Intelligent systems for anomaly detection of real cases for production optimizing

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UNED 2025 - Madrid

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Summary

Introduction

Introduction

Anomaly detection, fault detection, … to anomaly explanation

- What is an anomaly?
- What is a fault?
- What is the difference between an anomaly and a failure?
- What is anomaly/fault detection?
- Is the anomaly/fault explanation possible?
- The Fault-Tolerant Systems

Introduction

Anomaly detection, fault detection, … to anomaly explanation

Under a general point of view, anomaly detection, or fault detection, basically is the outlier identification as an observation, event, or data point that deviates from what is normal or expected, making it inconsistent with the rest of the data set.

Detecting anomalies or faults can have very important benefits.

Is it a simple task?

Introduction

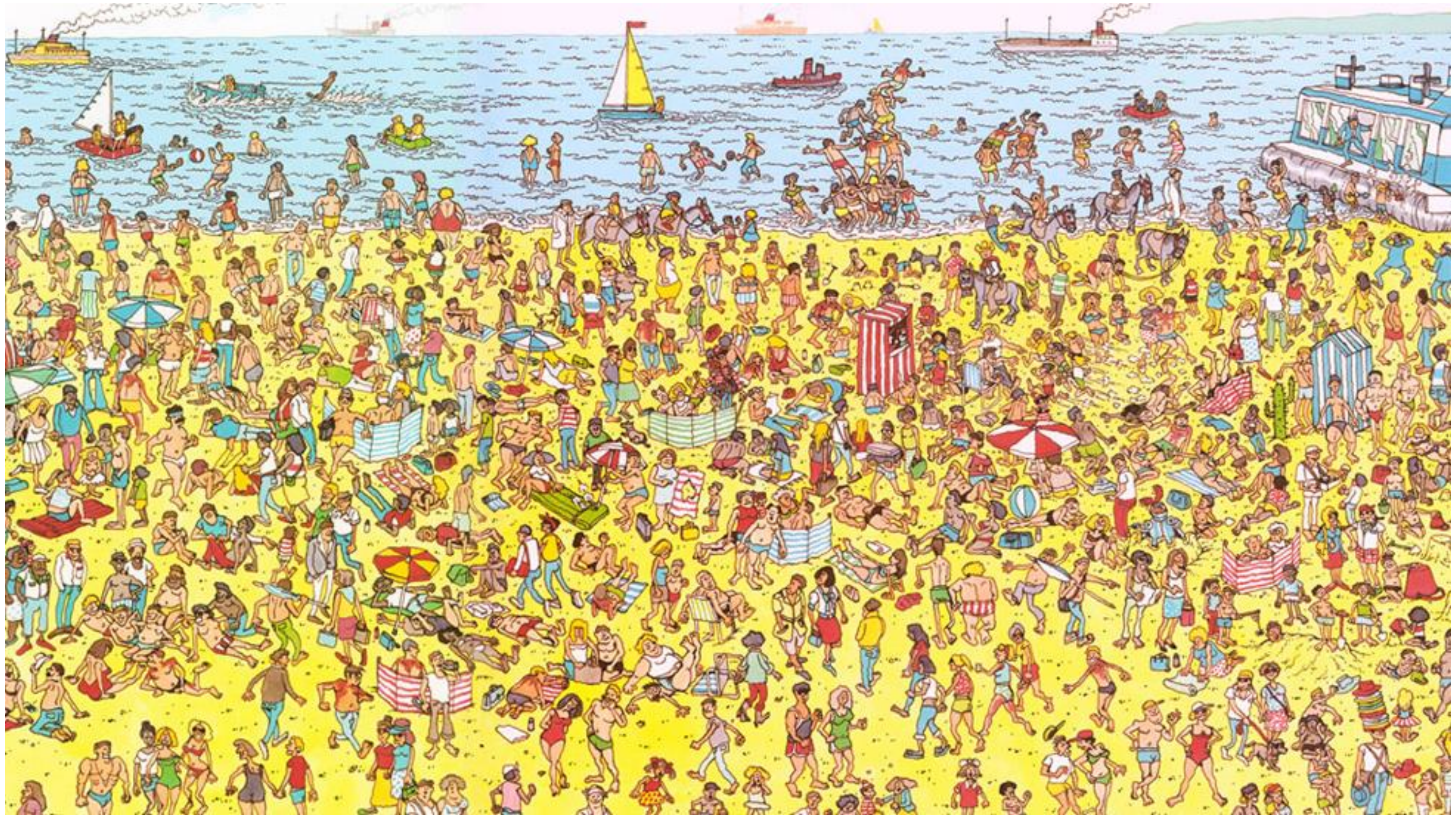
Anomaly detection, fault detection, … to anomaly explanation

It could be easy:

Introduction

Anomaly detection, fault detection, … to anomaly explanation

It could be not easy:



Where's Wally?

Introduction

Anomaly detection, fault detection, … to anomaly explanation

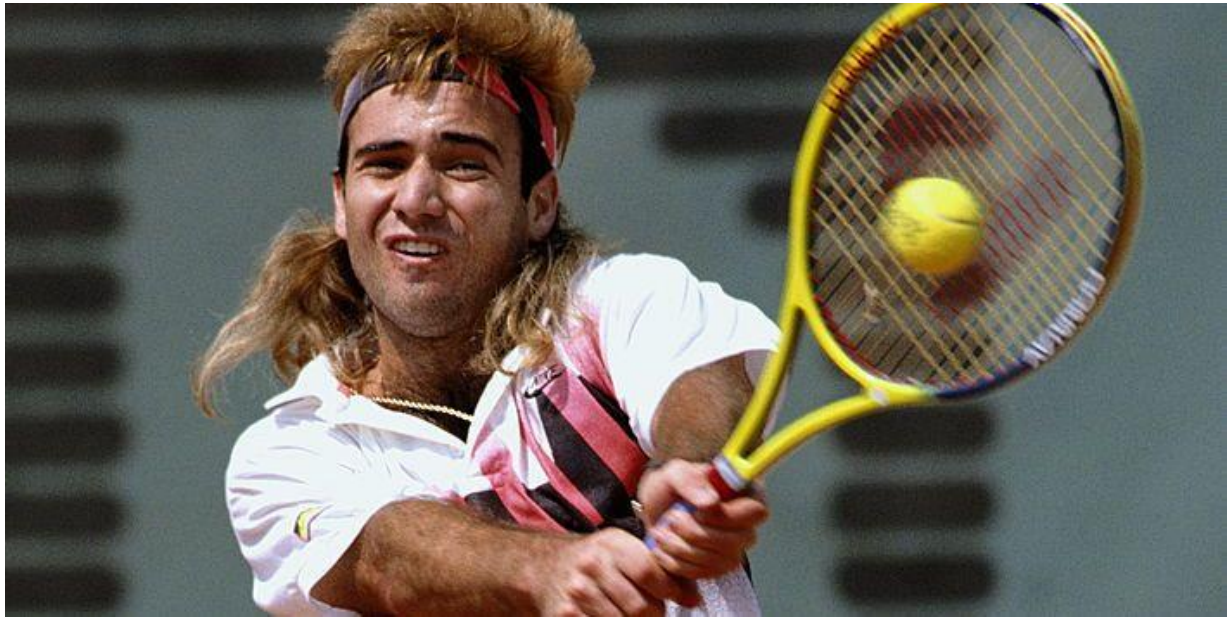
What happens if the problem is, for instance:

- Variable
- Not linear
- Multivariable dependent
- ….

Introduction

Anomaly detection, fault detection, … to anomaly explanation

Andre Agassi VS Boris Becker



https://www.puntodebreak.com/2020/04/30/lengua-becker-secreto-mejor-guardado-Agassi

Introduction

Anomaly detection, fault detection, … to anomaly explanation

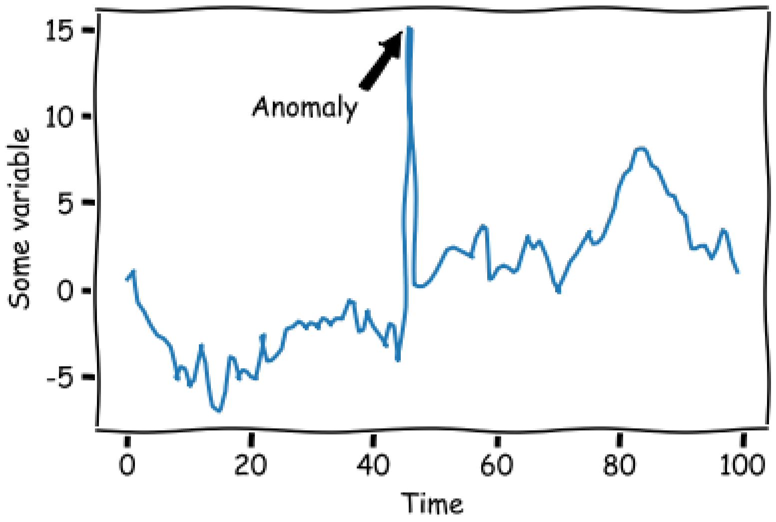
The unconscious secret of Boris Becker's tongue

Introduction

Anomaly detection, fault detection, … to anomaly explanation

Anomaly detection has a long history in the field of statistics.

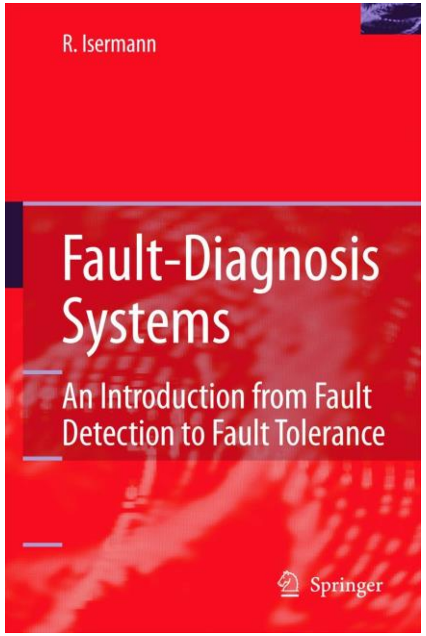
Analysts and scientists studied datasets and specially graphs, looking for anything that seemed abnormal.

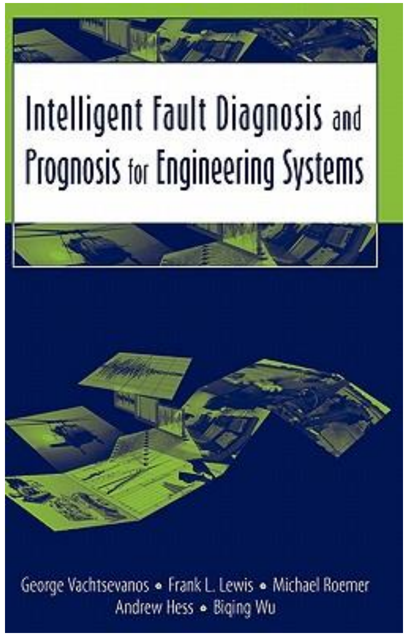


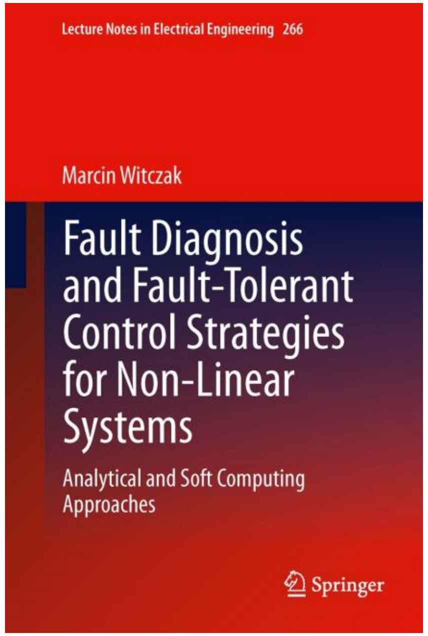
Introduction

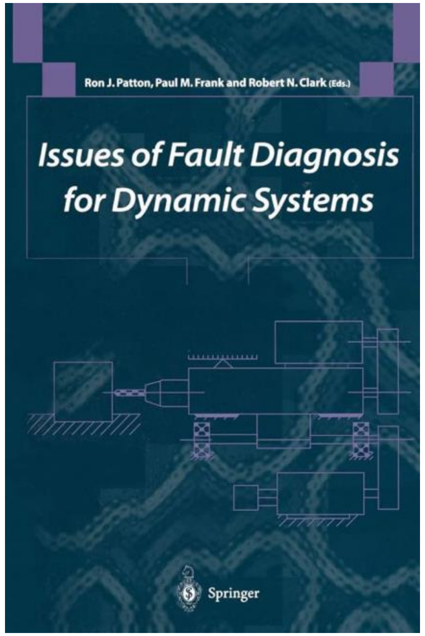
Anomaly detection, fault detection, … to anomaly explanation

It is a very important field in control systems.









Introduction

Anomaly detection, fault detection, … to anomaly explanation

Under a paradigm of control systems, in addition to the detection of faults and anomalies, the next issues are very important:

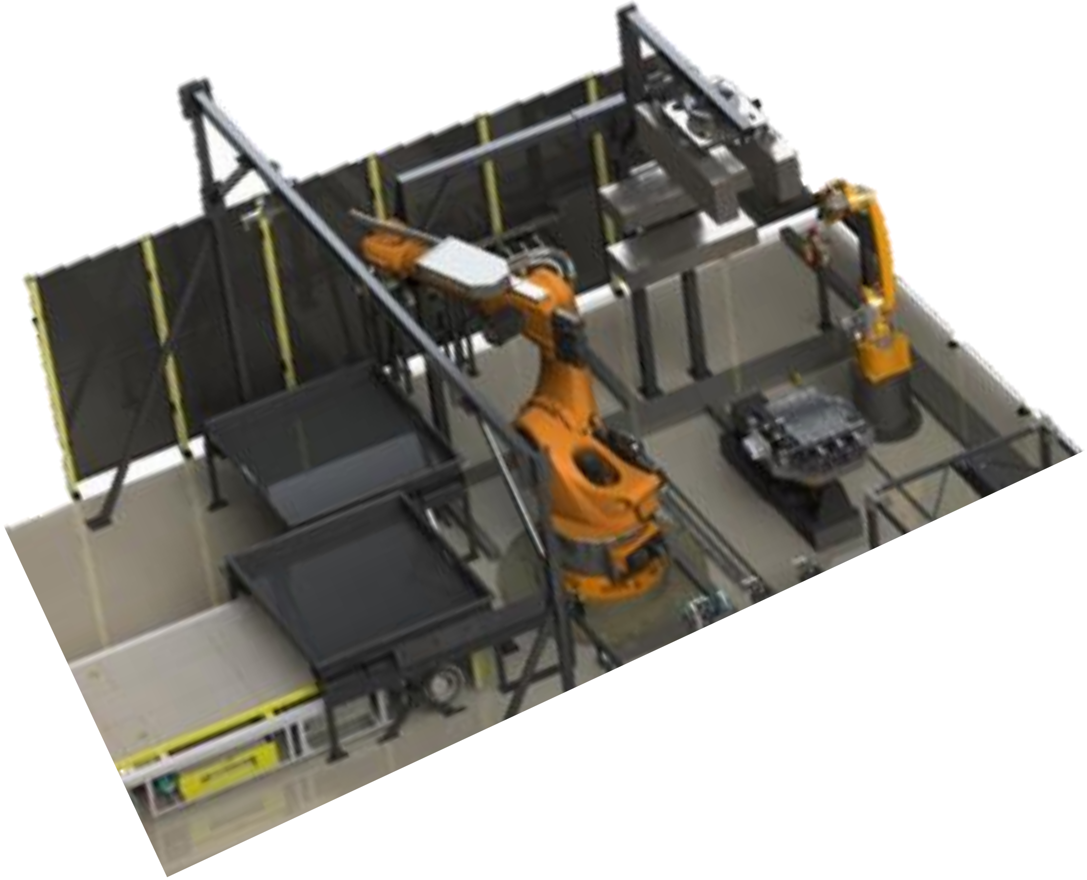
- Isolation
- Recovery

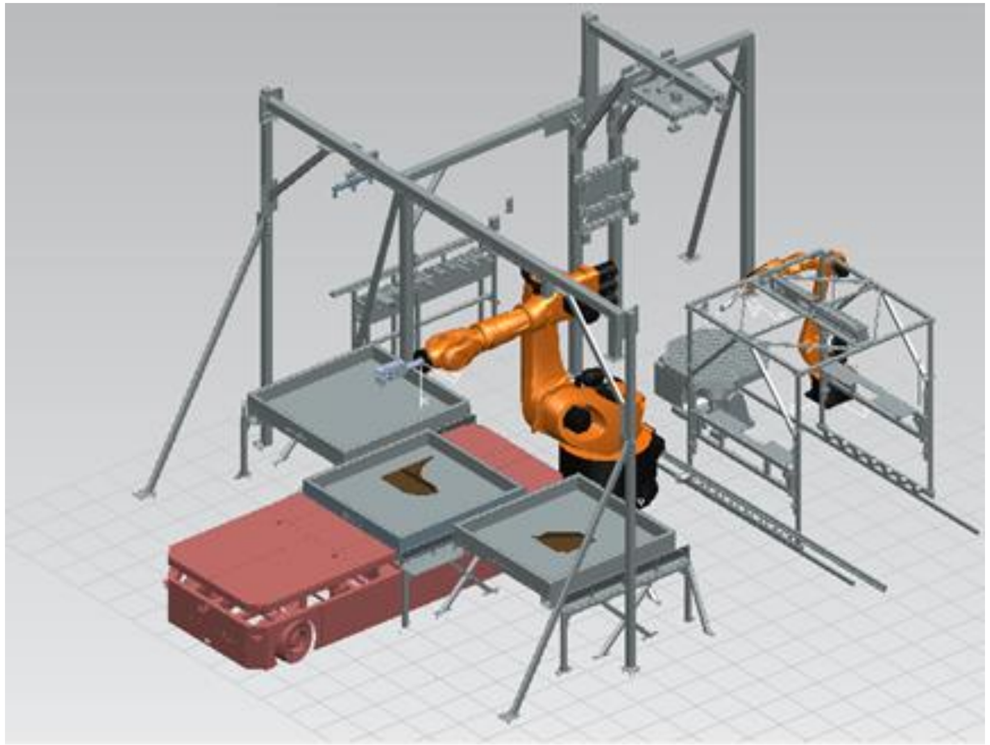
This leads to the very important subfield in the area of control systems called entitled "Fault detection, isolation, and recovery (FDIR)“.

Digital Twin research line CEMI (Navantia-UDC)

Digital Twin research line CEMI (Navantia-UDC)

Minor preassemblies parts manufacturing cell





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Minor preassemblies parts manufacturing cell

Transfer of materials into the welding cell

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Artificial Vision Gantry

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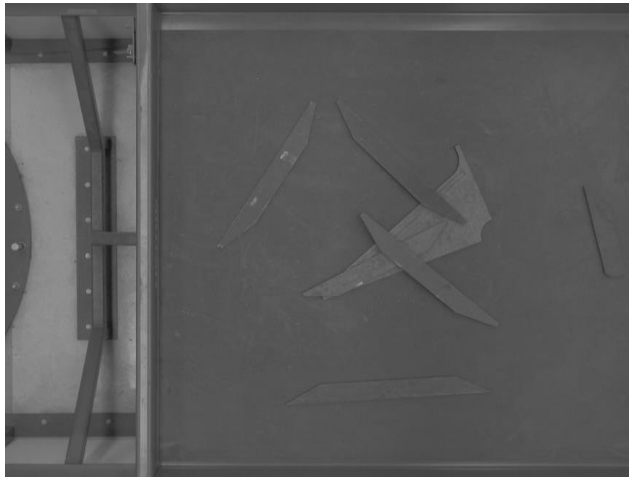
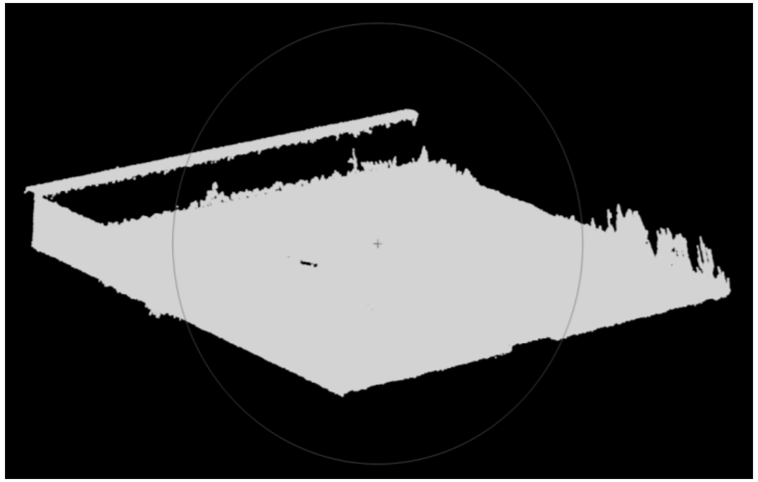
3D camera



2D Image of the Tray



Point Cloud of the Tray

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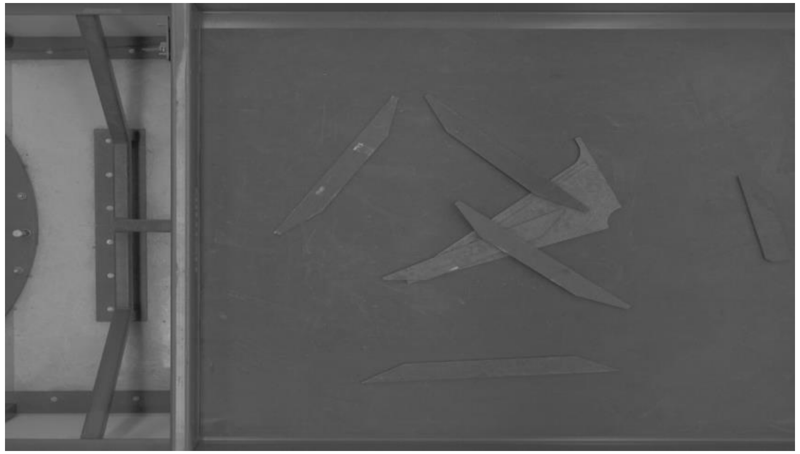
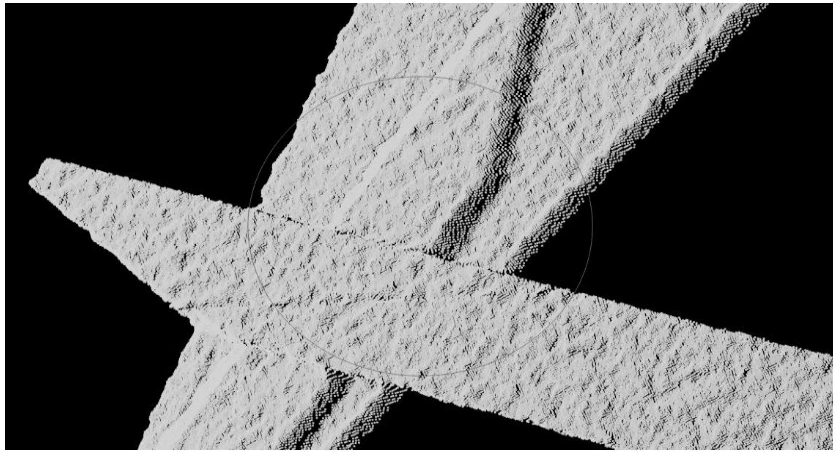
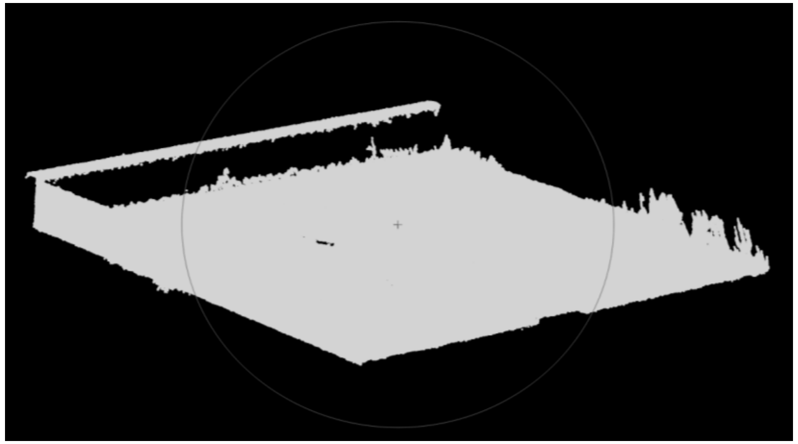
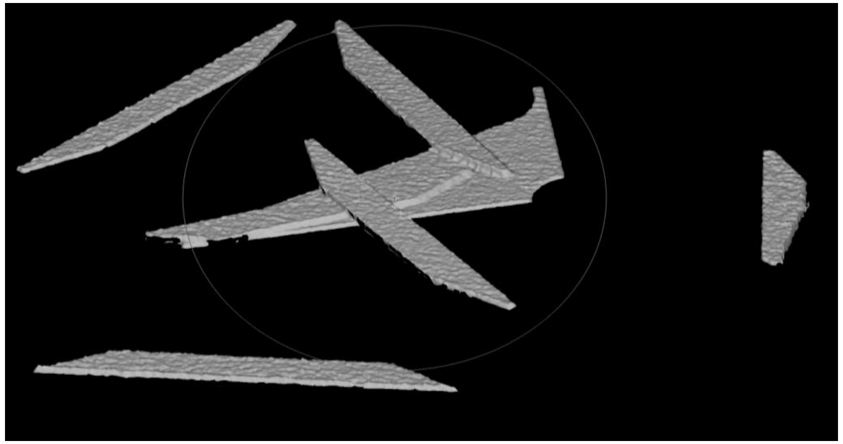

2D Monochromatic Image of the Tray


Zoom of the Processed Point cloud


Point Cloud of the Tray


Processed Point cloud of the elements in the tray

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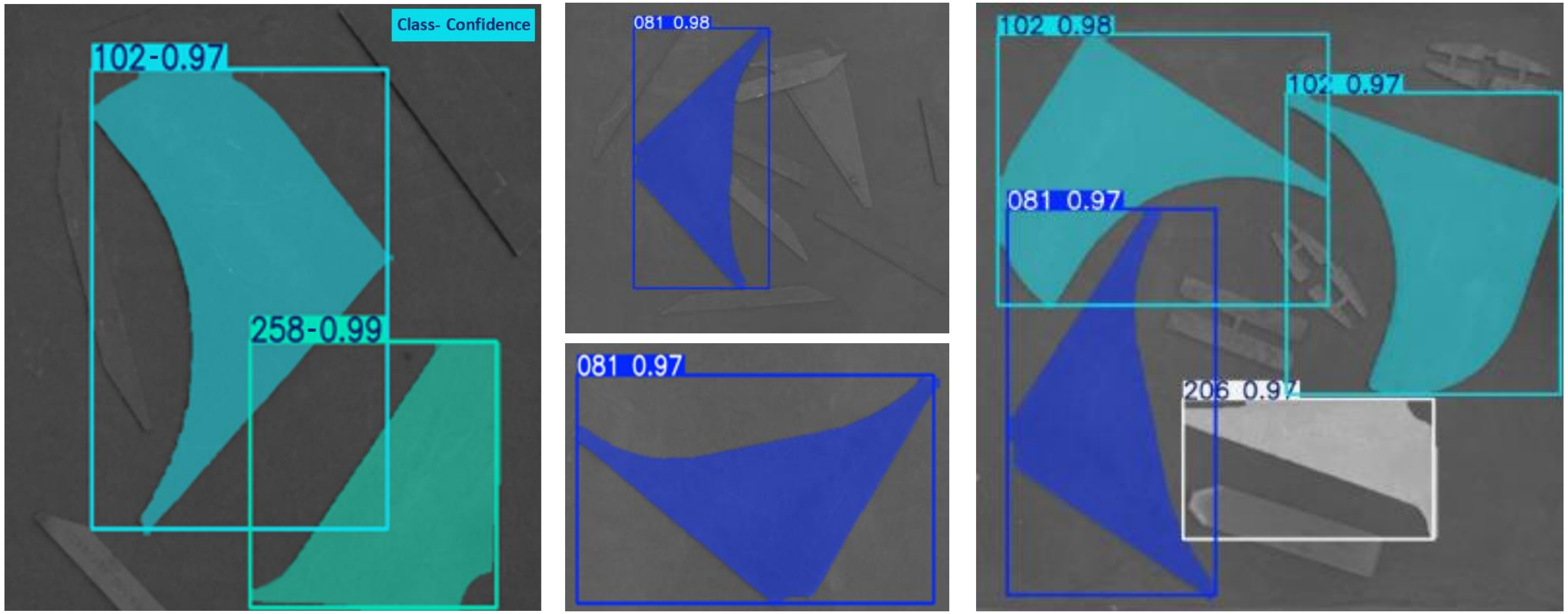
2D Tecniques

- ⇨ Convolutional Neural Networks
- ⇨ Transformers



Instance Segmentation *YOLOv8*

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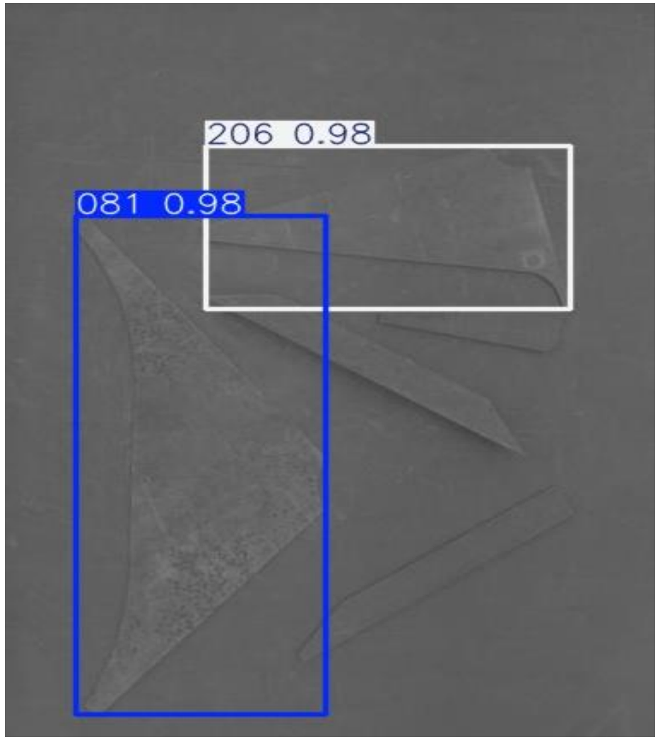
2D Tecniques

- Convolutional Neural Networks
- Transformers



Object Detection
RT-DETR

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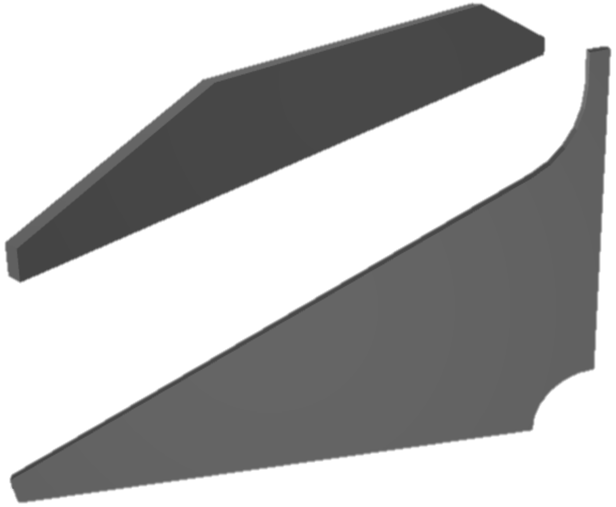
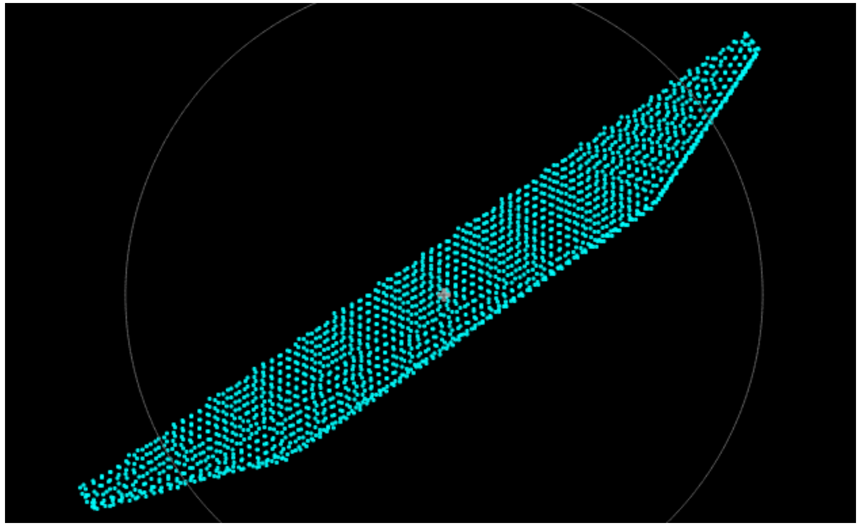
3D Tecniques
- Surface Matching
- 3D Edge Matching



CAD Models



Surface model

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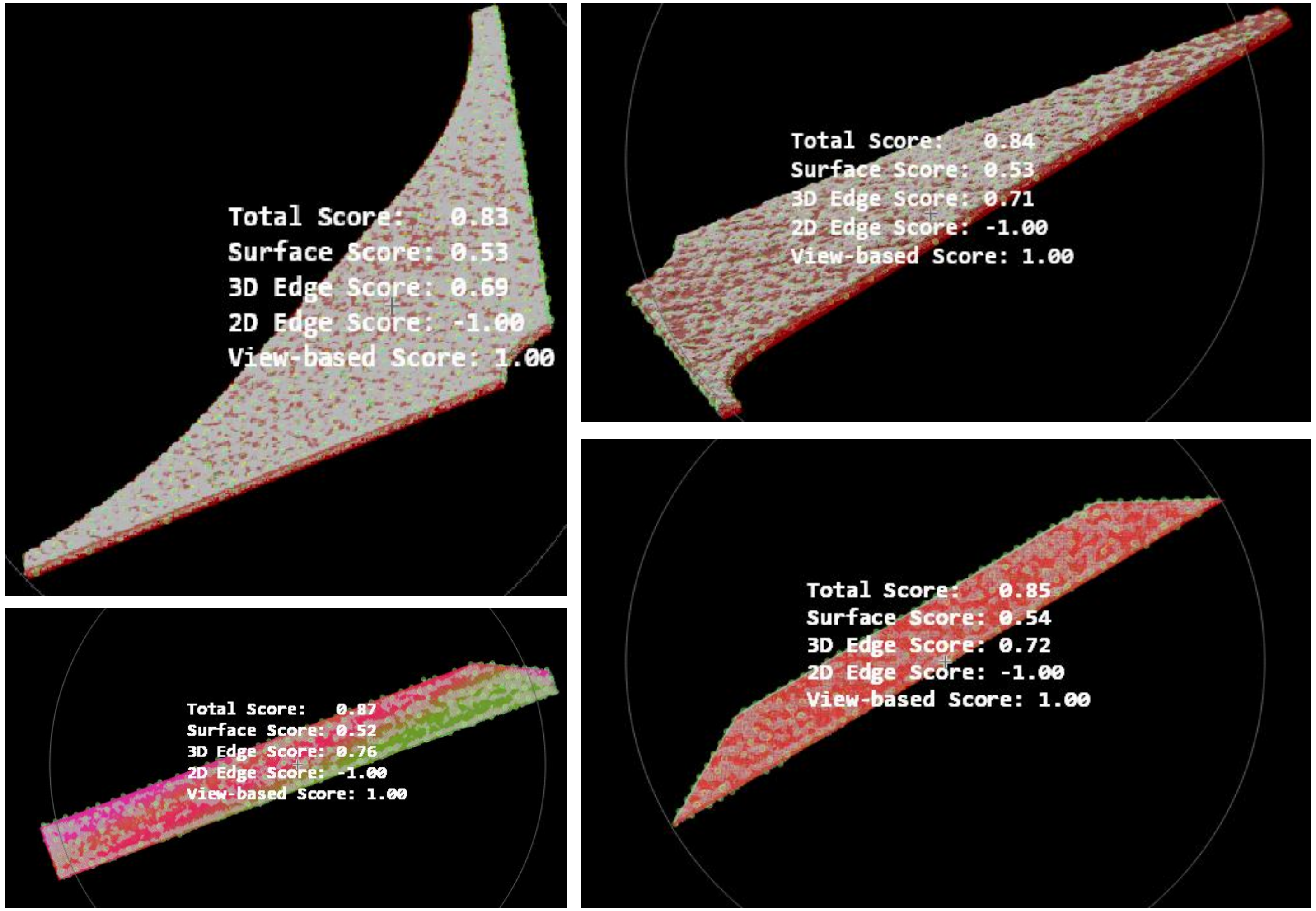

Matching Results

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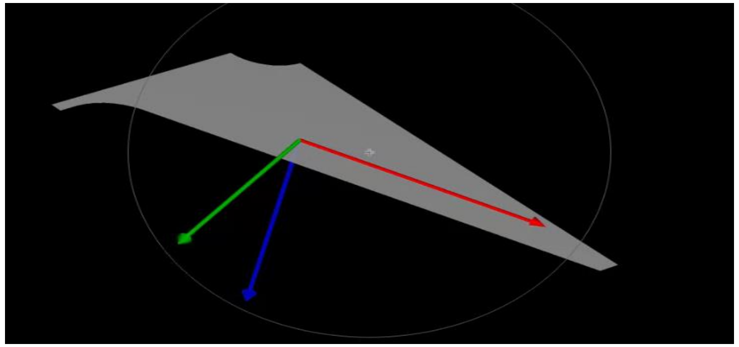
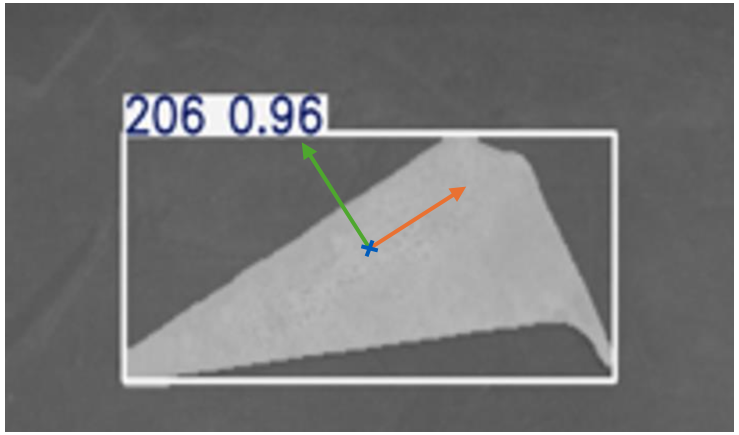
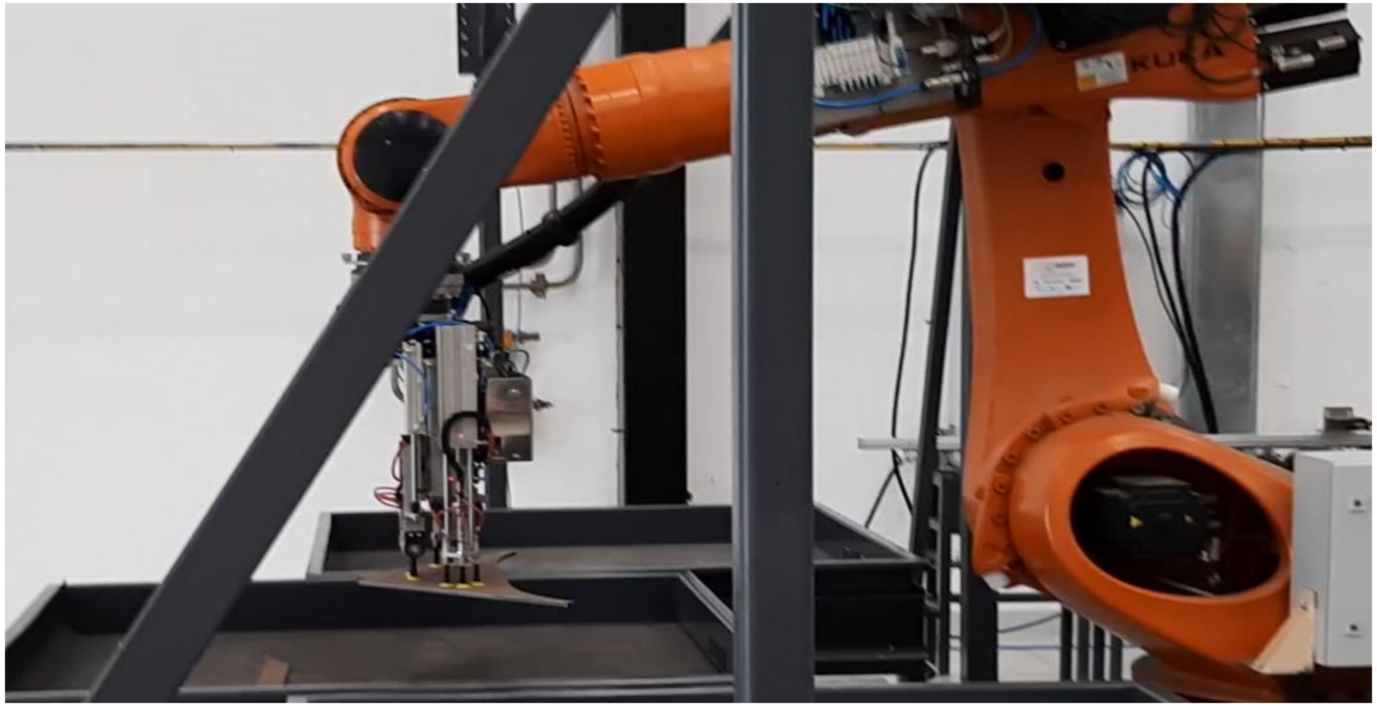




Orientation of the pieces



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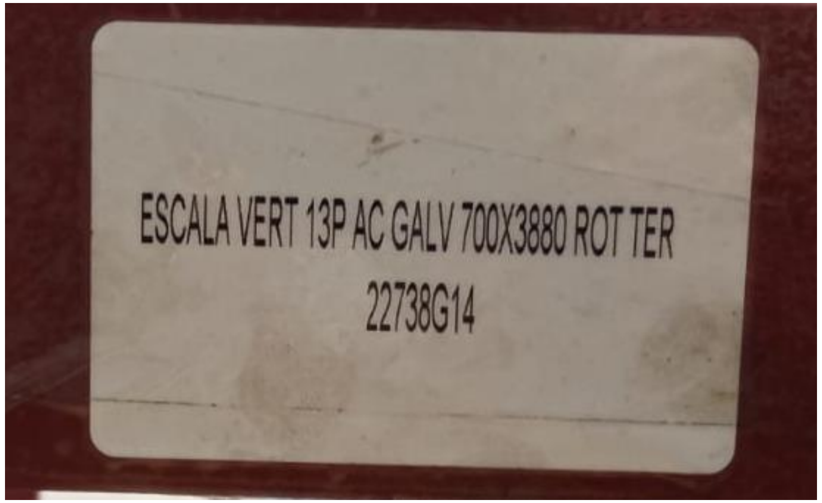
Optical Character Recognition



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Defect detection

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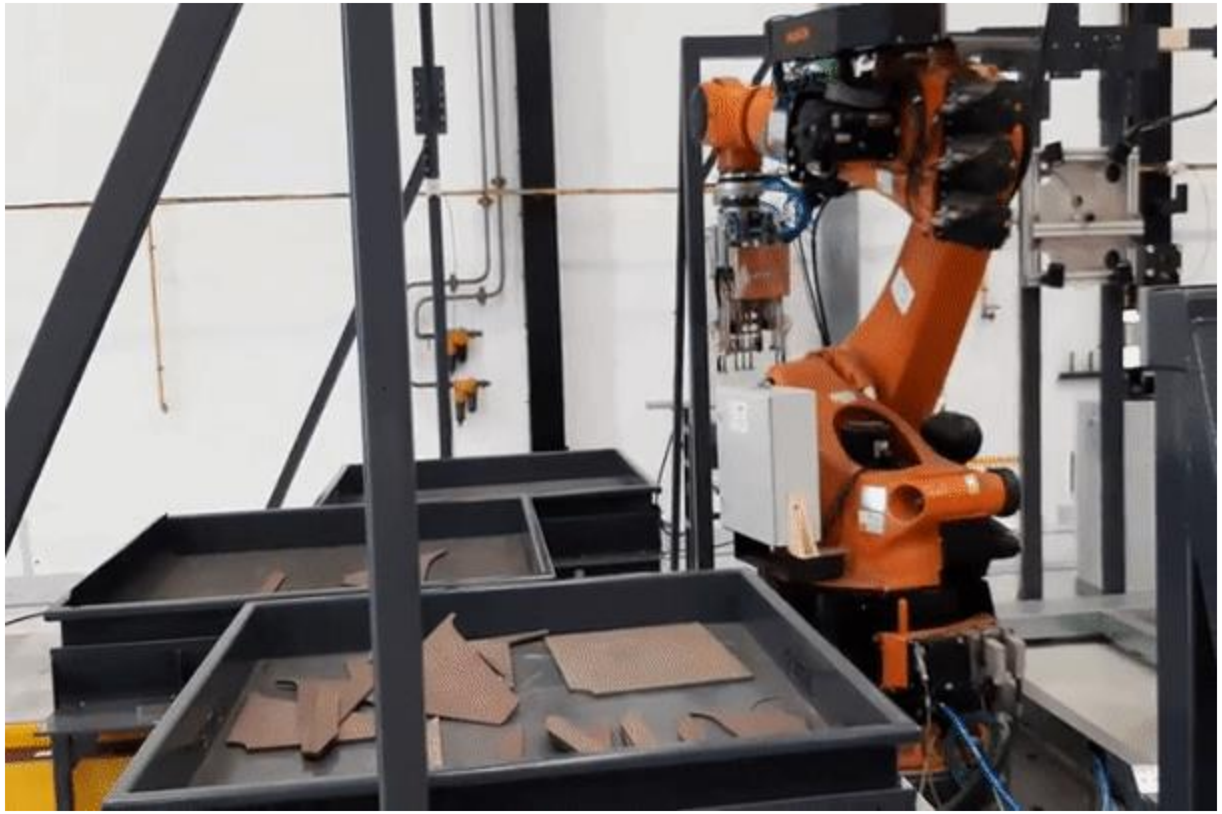
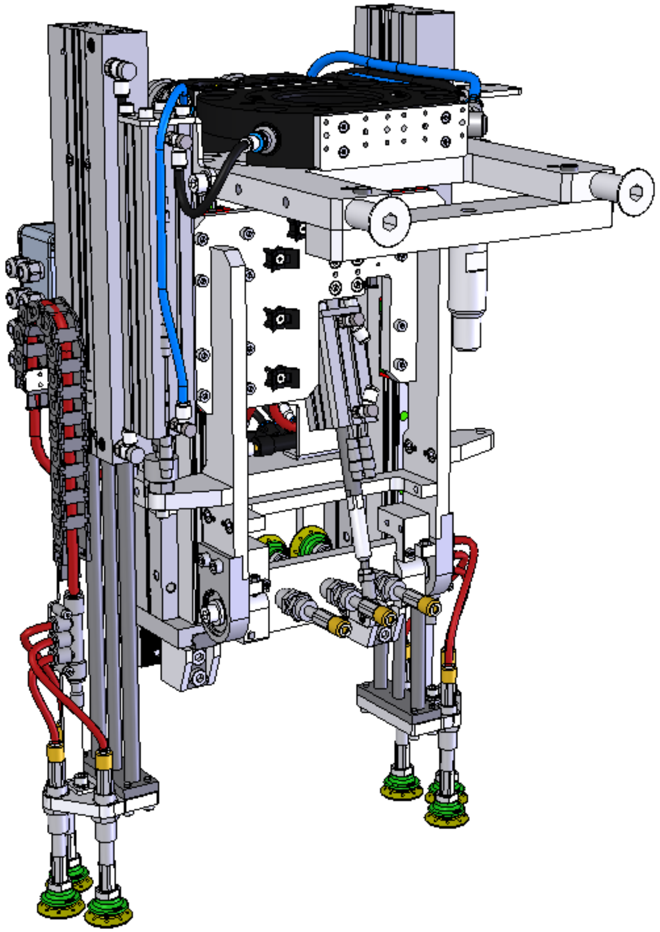


Base plates pick up



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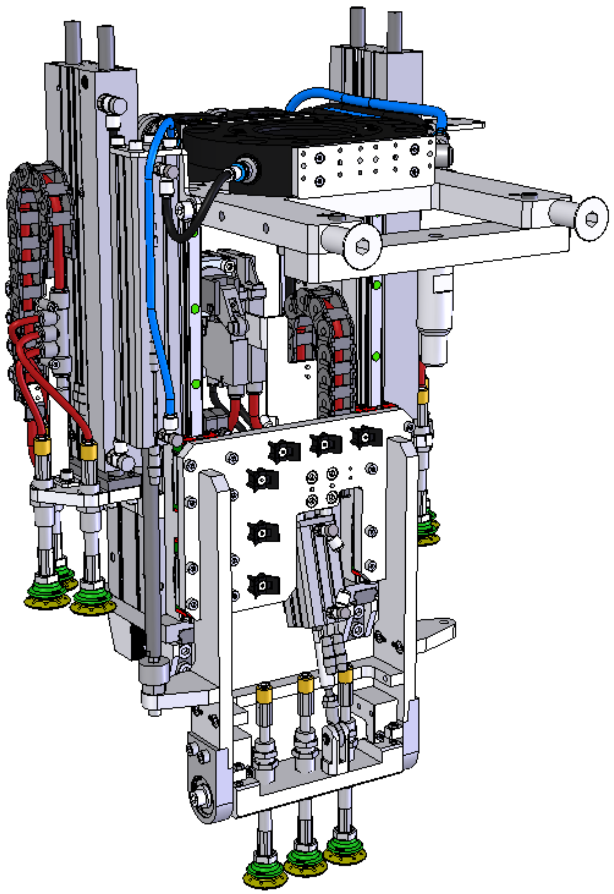

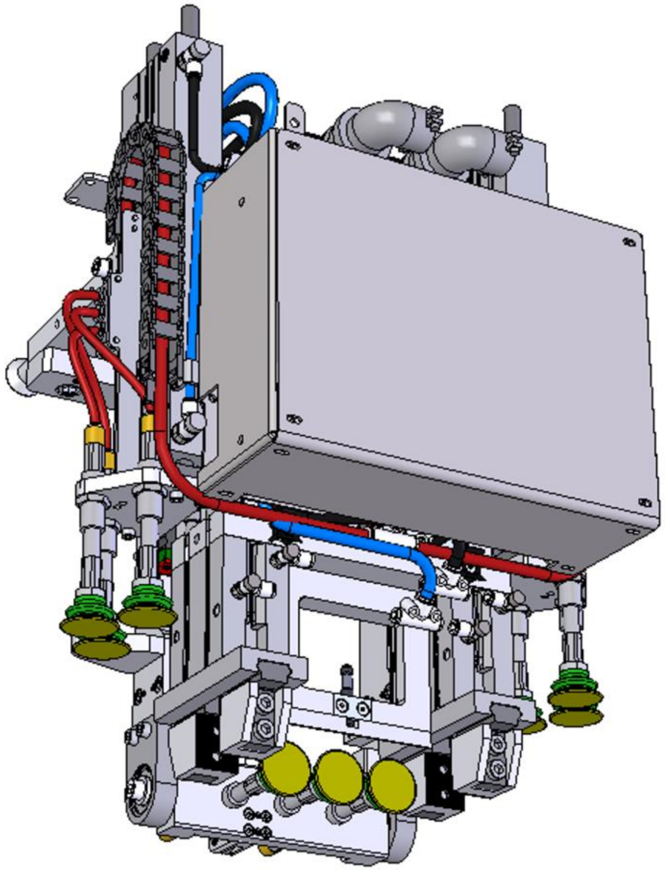

Reinforcements pick up

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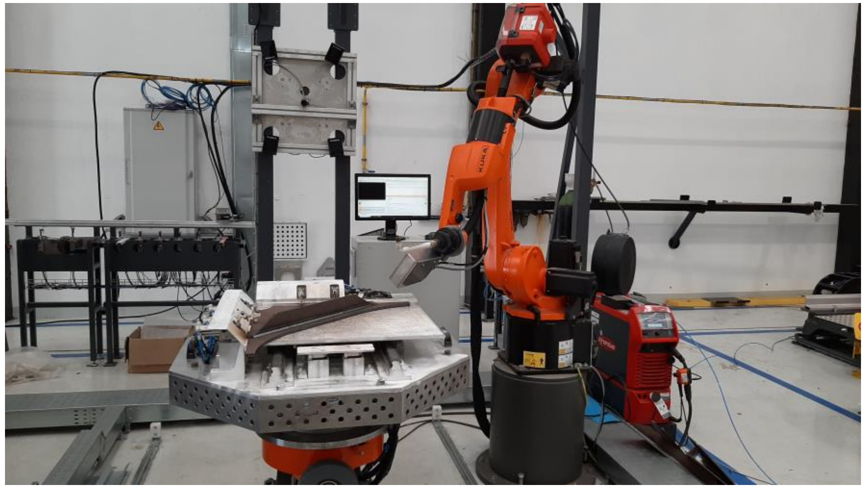
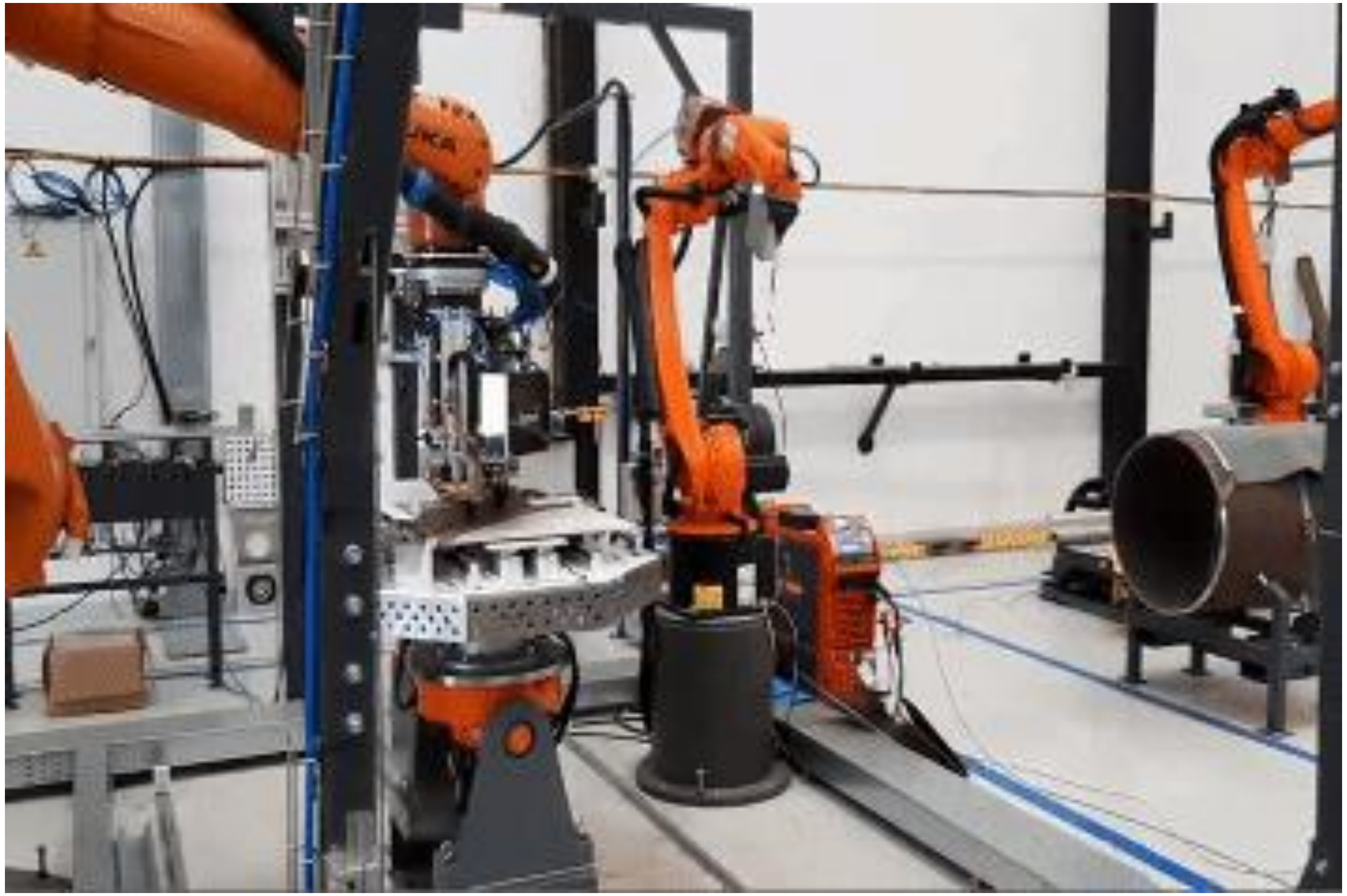
Minor preassemblies parts manufacturing cell

Reinforcements pick up

Digital Twin research line CEMI (Navantia-UDC)

Minor preassemblies parts manufacturing cell





Application of traditional/intelligent techniques for the detection of failures or anomalies in welding

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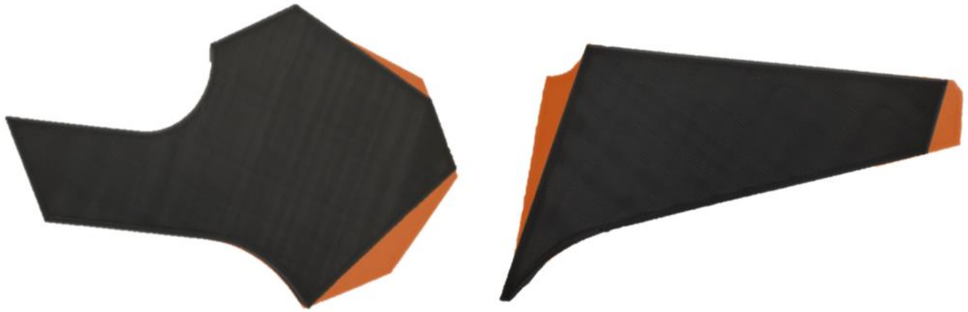
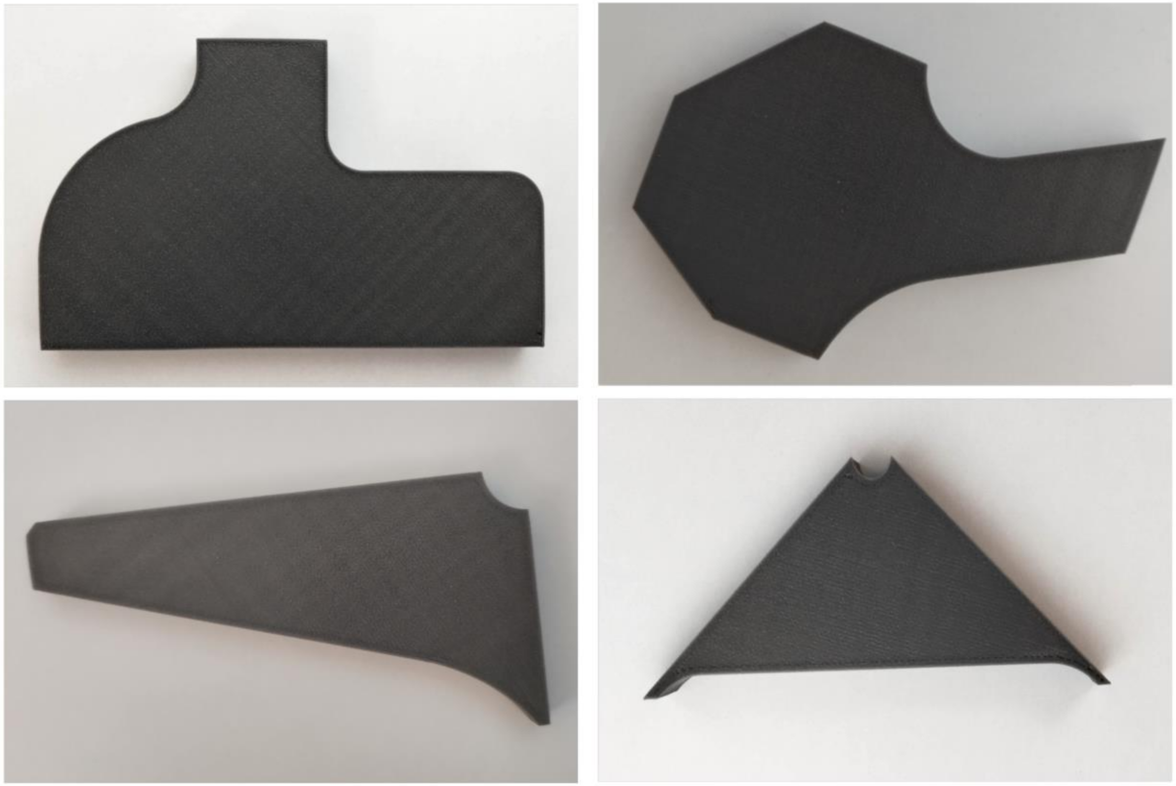
Laboratory tests (Due to Navantia confidenciality)

Intel RealSense D455 Depth Camera



Defective Piece with Highlighted Defects in Orange



Images of the four different 3D printed pieces.

Our proposals for Fault Detection accomplishing

Our proposals for Fault Detection accomplishing

Techniques and implementation

What kind of FD techniques we use:

- Traditional ones based on statistical methods
- Based on intelligent techniques

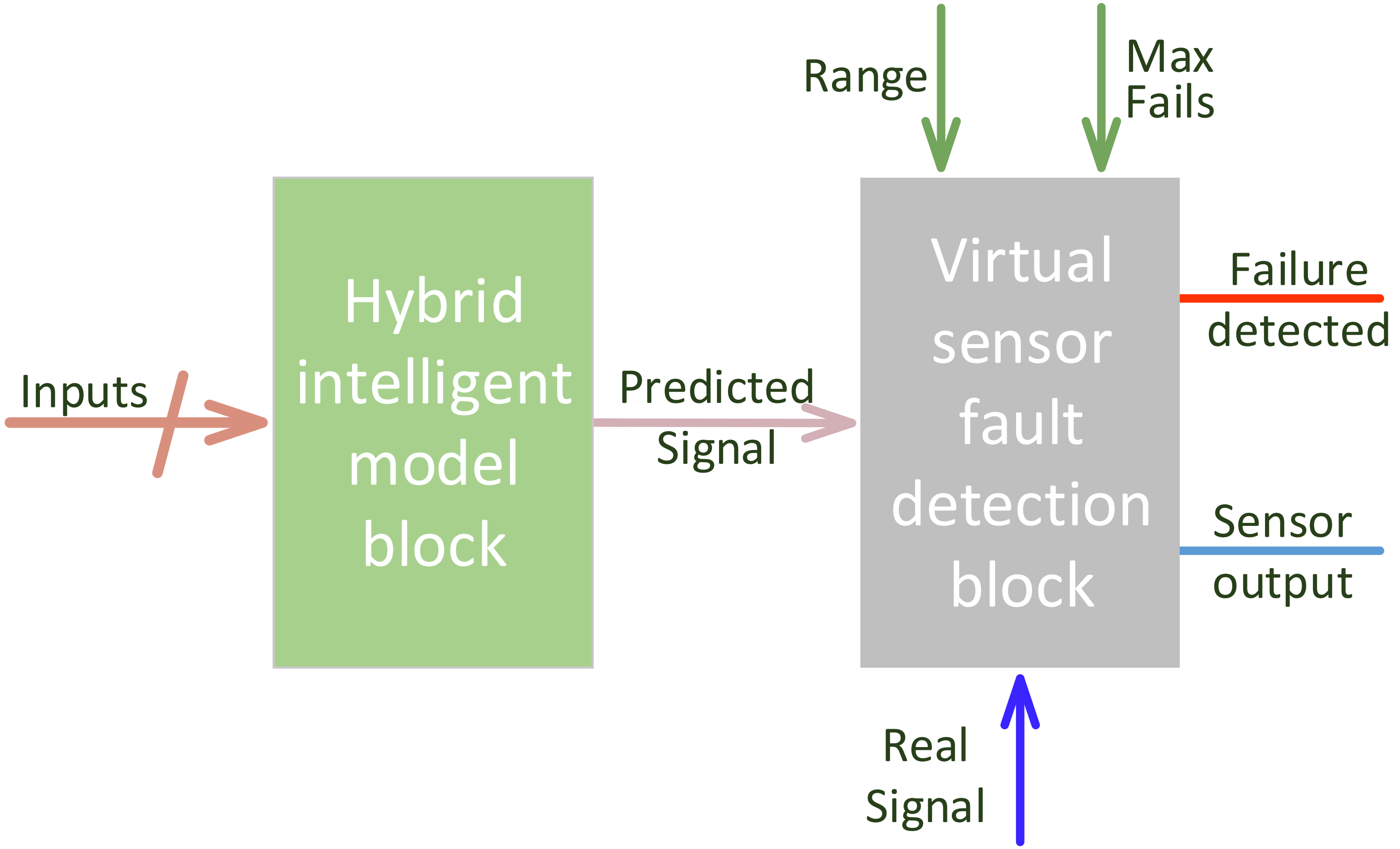
The implementation attending to the topology:

- Based on models
- Based on One-class techniques

Based on model

Based on model

Anomaly detection based on virtual sensors

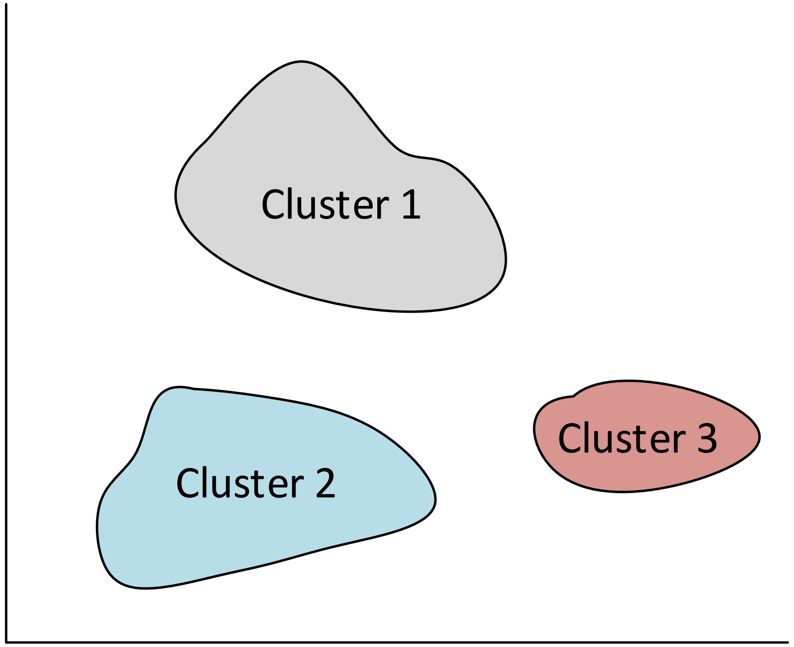


Based on model

Anomaly detection based on virtual sensors

Hybrid intelligent model block.

- Modeling process.

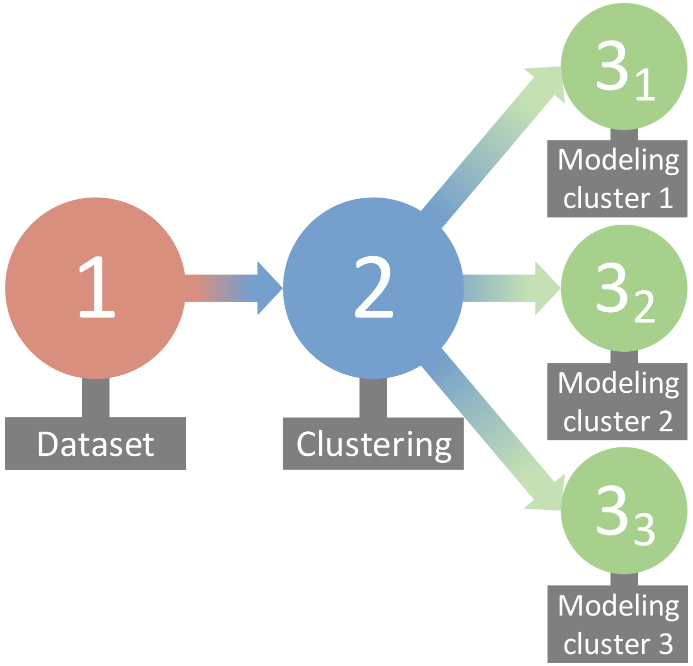


Based on model

Anomaly detection based on virtual sensors

Hybrid intelligent model block.

- Modeling process.

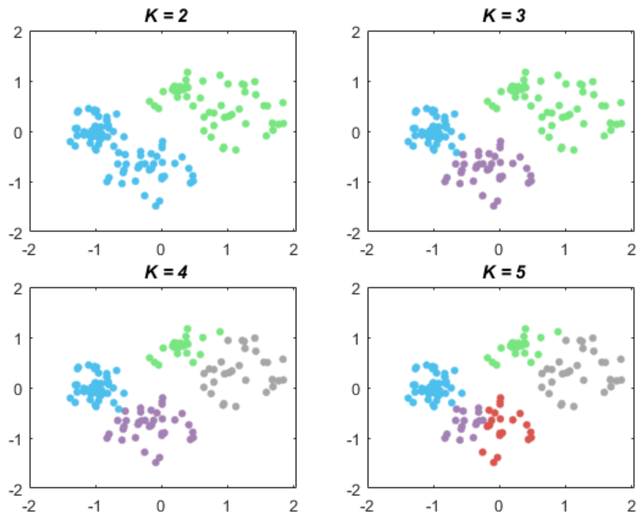


Based on model

Anomaly detection based on virtual sensors

Hybrid intelligent model block.

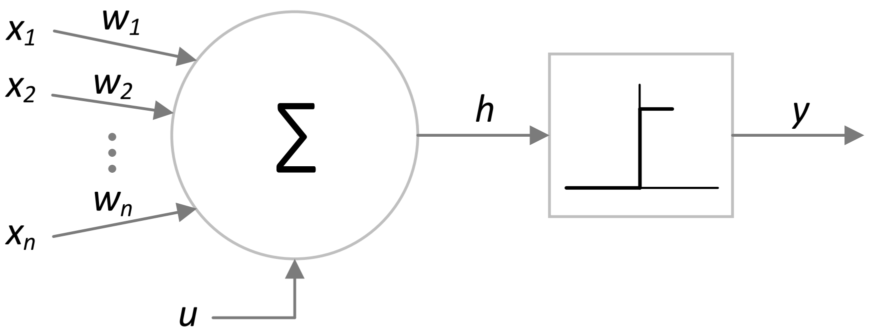
- Modeling process → Clustering → Kmeans



$$E(c_1, ..., c_K) = \sum_{i=1}^{N} \sum_{j=1}^{K} I(x_i \in G_j) \, ||x_i - c_j||$$

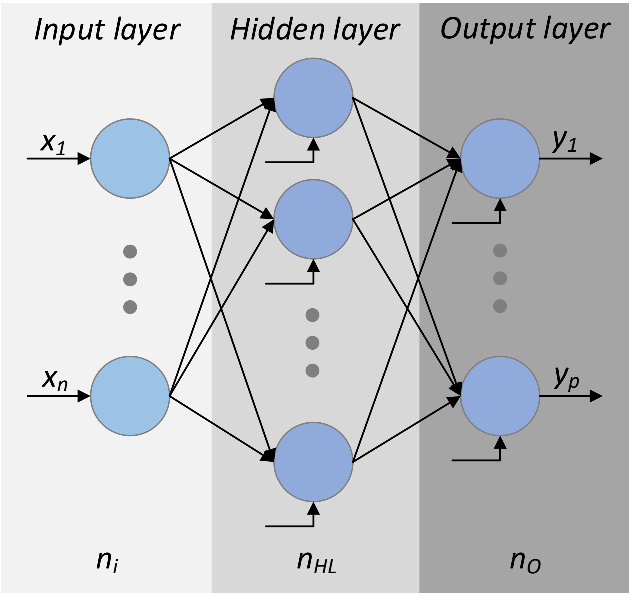
Hybrid intelligent model block.

- Modeling process → Modeling → MLP



$$h = f_{\theta 1}\left(xW_1 - u_1\right)$$

$$y = f_{\theta 2}\left(hW_2 - u_2\right)$$

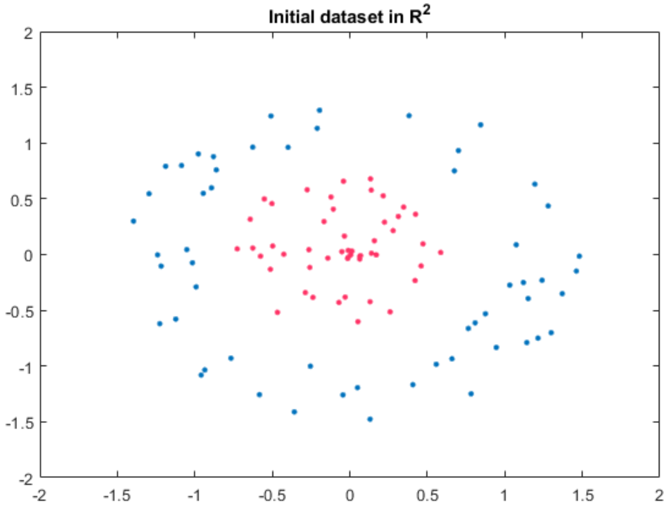


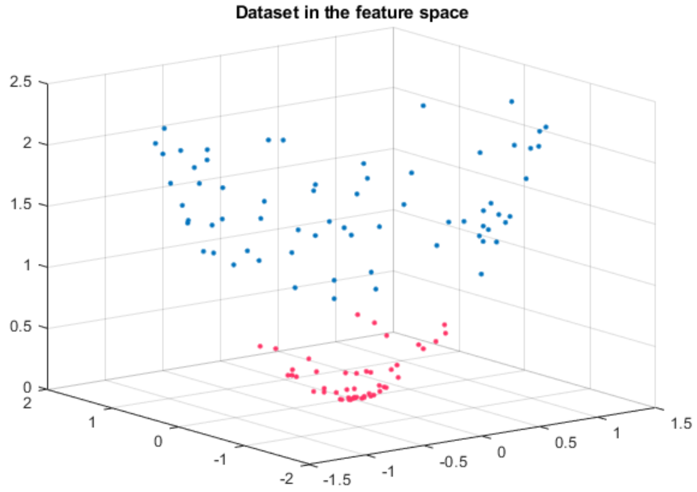
Based on model

Anomaly detection based on virtual sensors

Hybrid intelligent model block.

- Modeling process → Modeling → LS SVR

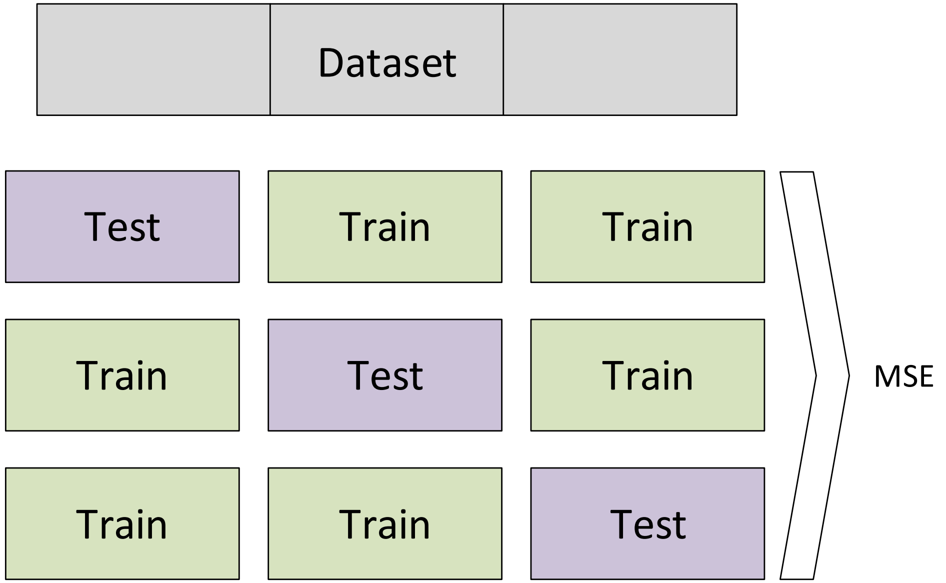




$$y = f(X) = w^T \delta(x) + b$$

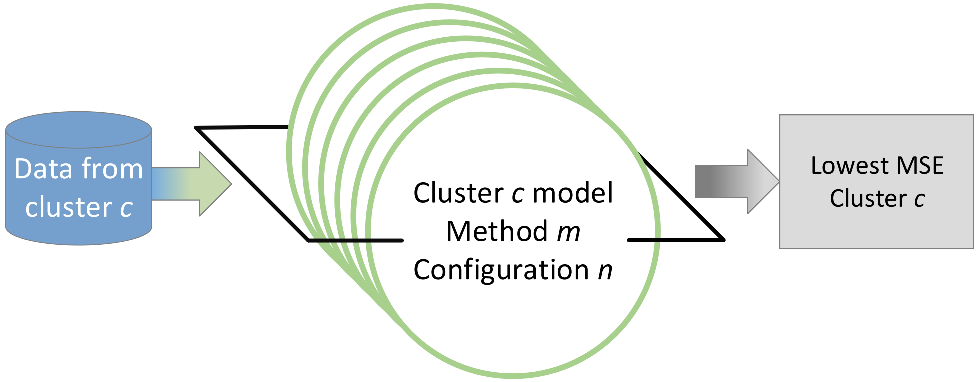
Hybrid intelligent model block.

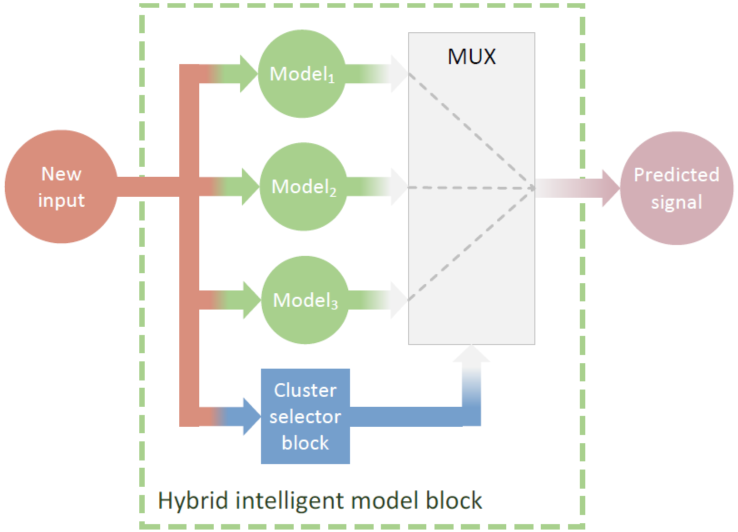
- Modeling process → Modeling → Validation



Hybrid intelligent model block.

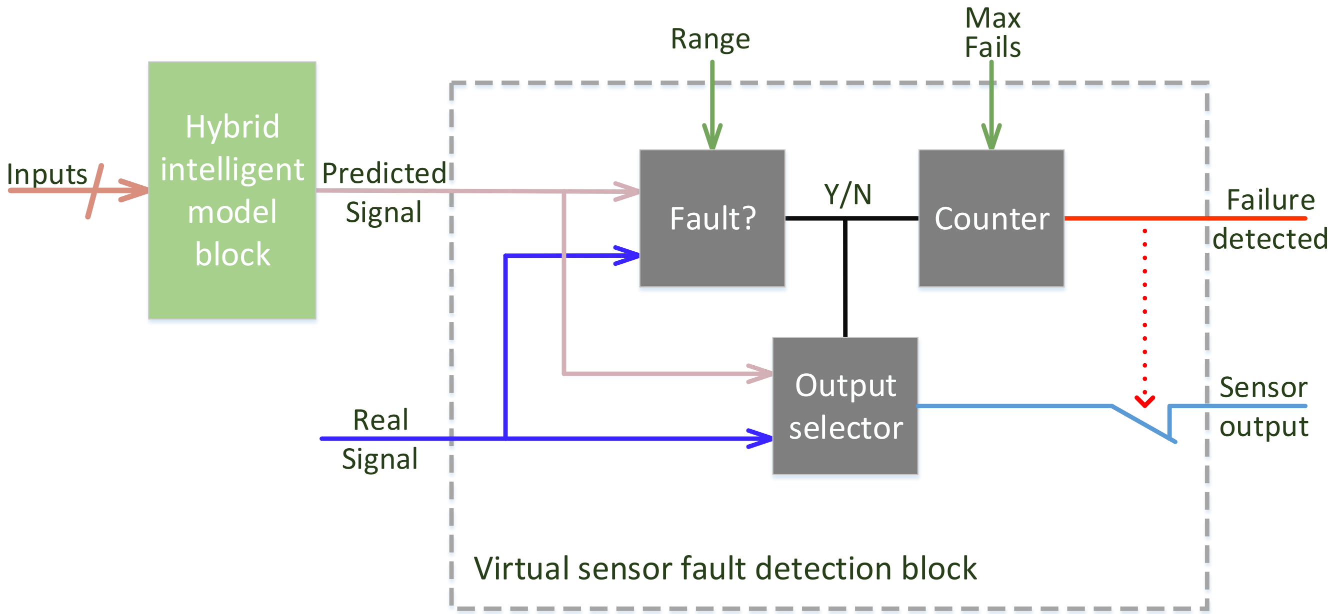
- Modeling process → Modeling → Best configuration





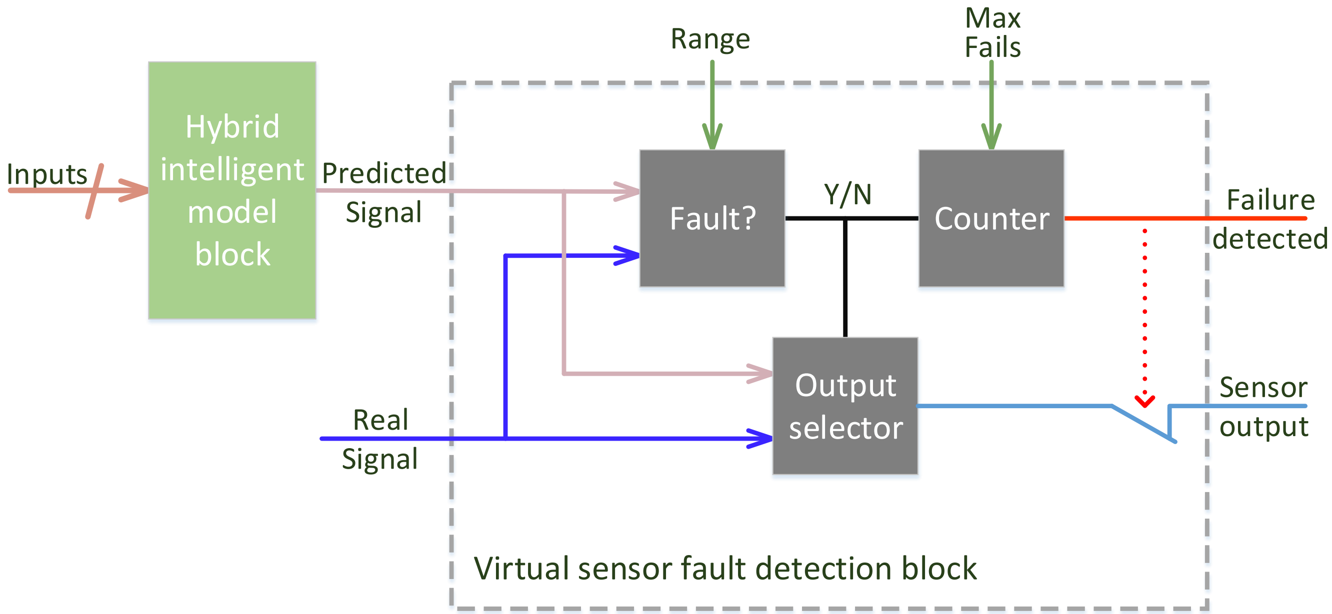
Virtual sensor fault detection block.

- Virtual sensor fault detection block → Fault block



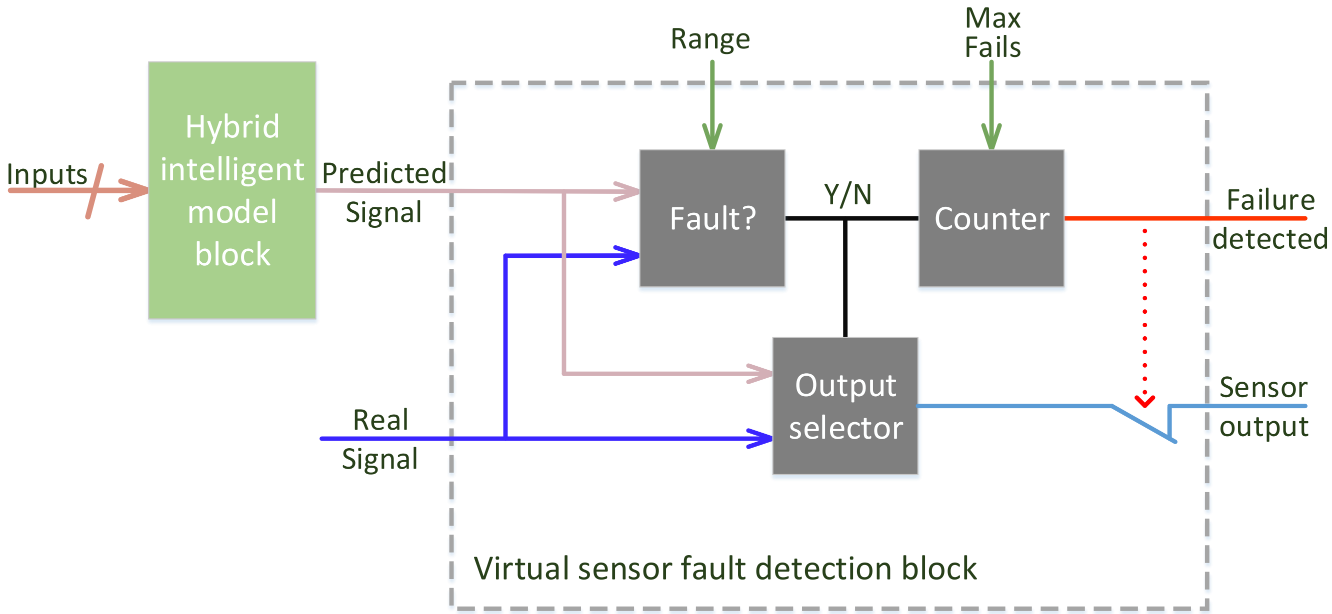
Virtual sensor fault detection block.

- Virtual sensor fault detection block → Counter block



Virtual sensor fault detection block.

- Virtual sensor fault detection block → Output selector block

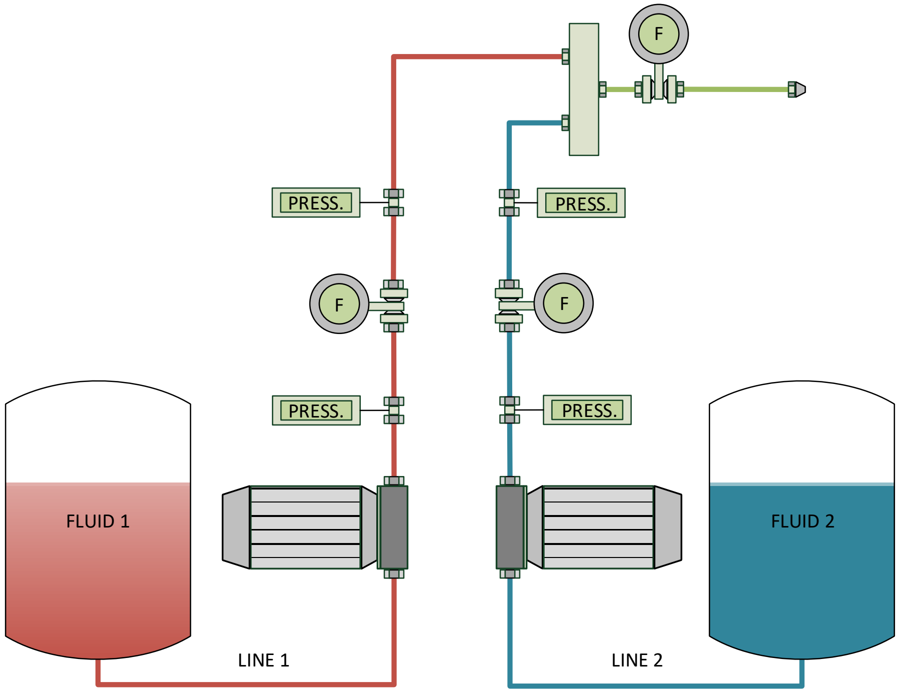


Based on model

Anomaly detection based on virtual sensors

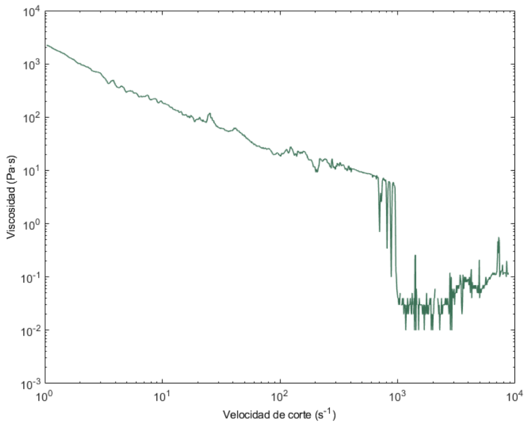
Bicomponent mixing system → Real case of application

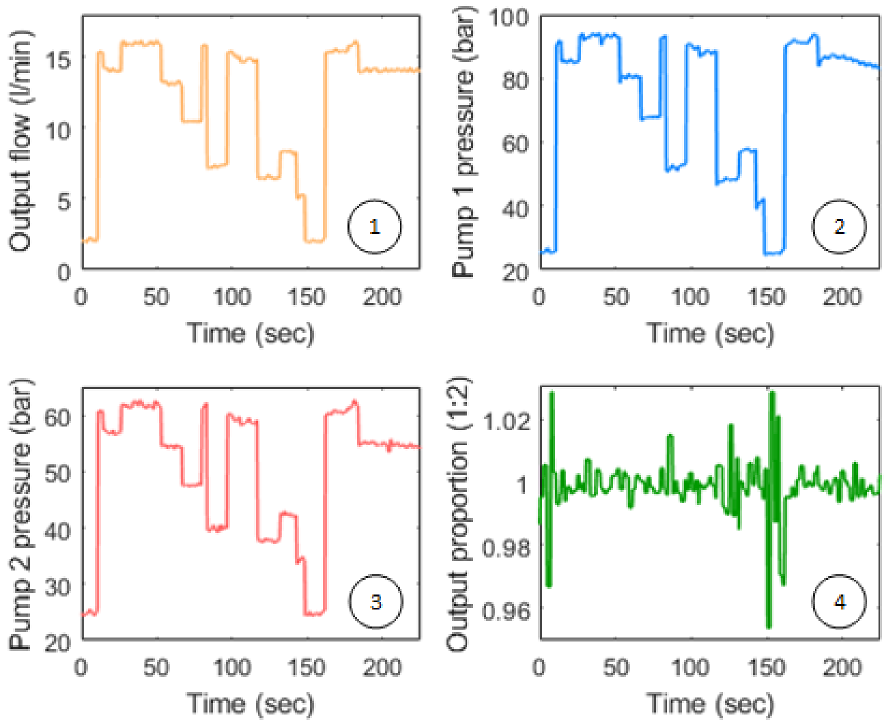
- Virtual sensor for fault detection, isolation and data recovery for bicomponent mixing machine monitoring



Bicomponent mixing system

- Monitored variables.
  - Mixing proportions.
  - Two pump speeds.
  - Three flows.
  - Four pressures.
- Dataset: 8549 samples.





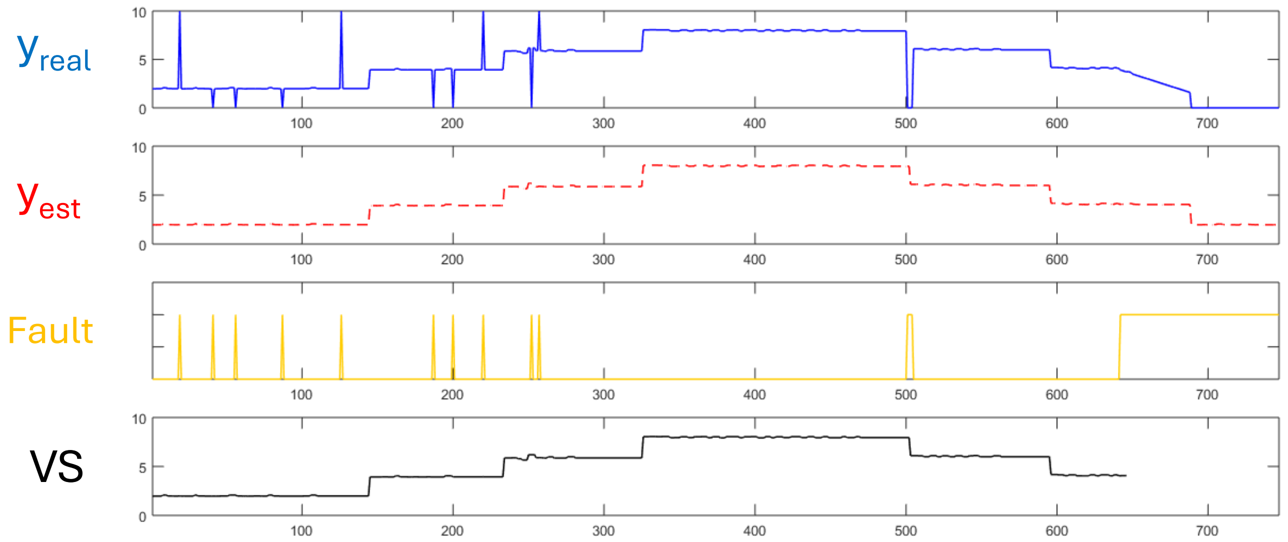
Bicomponent mixing system

- Experiments and results.
  - Model inputs.
    - Output flow, Flow 2 (t, t-1, t-2).
    - Pumps pressures 1 and 2 (t, t-1, t-2).
    - Flowmeters pressures 1 and 2 (t, t-1, t-2).
    - Flow 1 (t-1, t-2).
  - Model Output.
    - Flow 1 (t).
  - Techniques
    - Kmeans → Clusters: 1:1:10.
    - MLP → Hidden layer neurons: 1:1:15 / Different activation functions.
    - LS-SVR → Self-tuned optimization toolbox.

Bicomponent mixing system

- Experiments and results.
  - Best configuration.
    - 7 clusters.
    - MSE = 0,131·10-3.

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7
Technique	ANN-1	ANN-1	ANN-7	ANN-5	ANN-3	ANN-3	ANN-8
MSE	$0.165 \cdot 10^{-3}$	$0.159 \cdot 10^{-3}$	$0.097 \cdot 10^{-3}$	$0.55 \cdot 10^{-3}$	$0.183 \cdot 10^{-3}$	$0.163 \cdot 10^{-3}$	$0.122 \cdot 10^{-3}$



Based on One-class techniques

Fundamentals

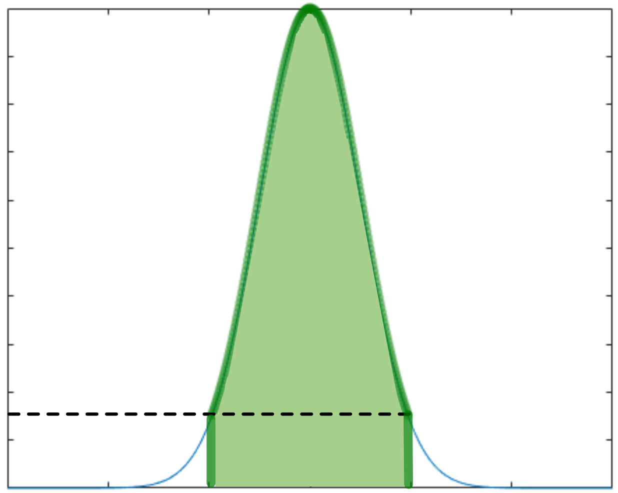
- One-class:
  - Density estimation methods.
  - Reconstruction methods.
  - Boundary methods.

Based on One-class techniques

Anomaly detection based on One-class techniques

Fundamentals

- One-class:
  - **Density estimation methods.**
  - Reconstruction methods.
  - Boundary methods.



Based on One-class techniques

Anomaly detection based on One-class techniques

Fundamentals

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  - **Reconstruction methods.**
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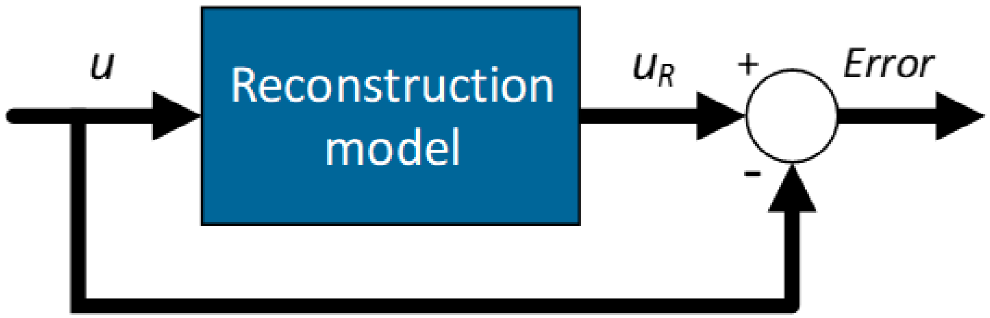

Based on One-class techniques

Anomaly detection based on One-class techniques

Fundamentals

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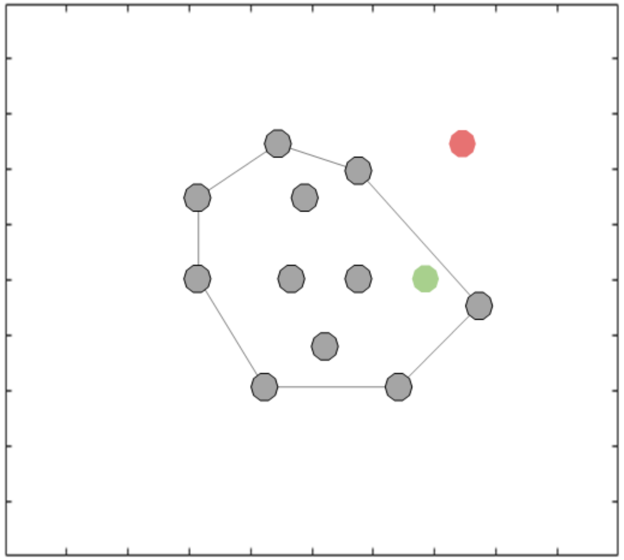
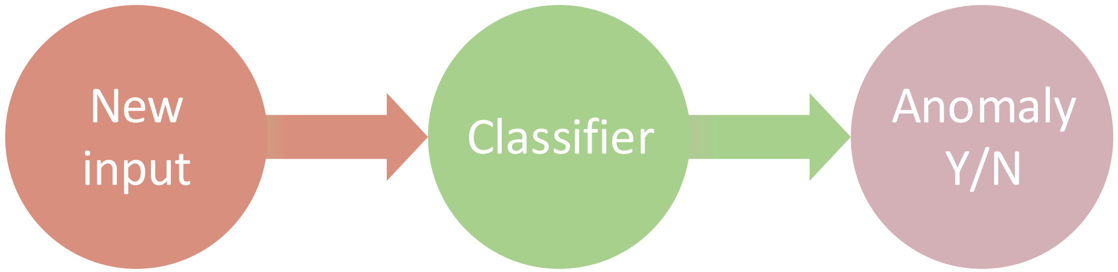
  - Density estimation methods.
  - Reconstruction methods.
  - **Boundary methods.**



Based on One-class techniques

Anomaly detection based on One-class techniques

Fundamentals

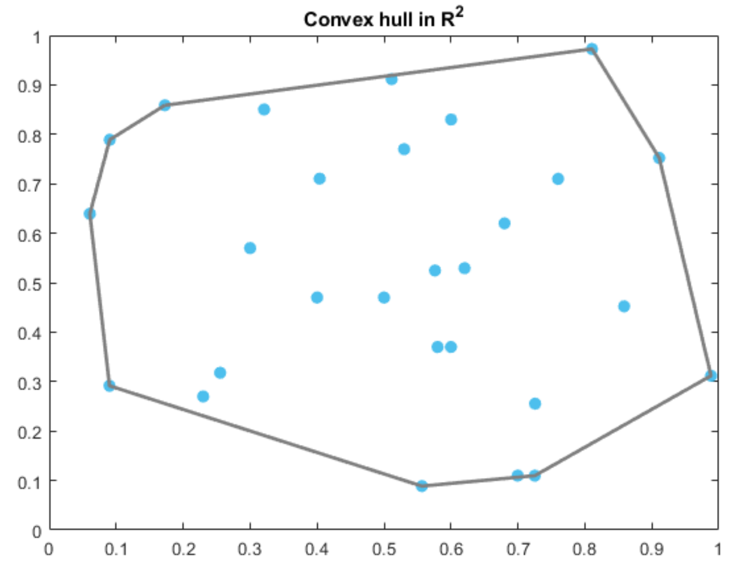


Based on One-class techniques

Anomaly detection based on One-class techniques

Implementation

- One-class techniques.
  - ACH.



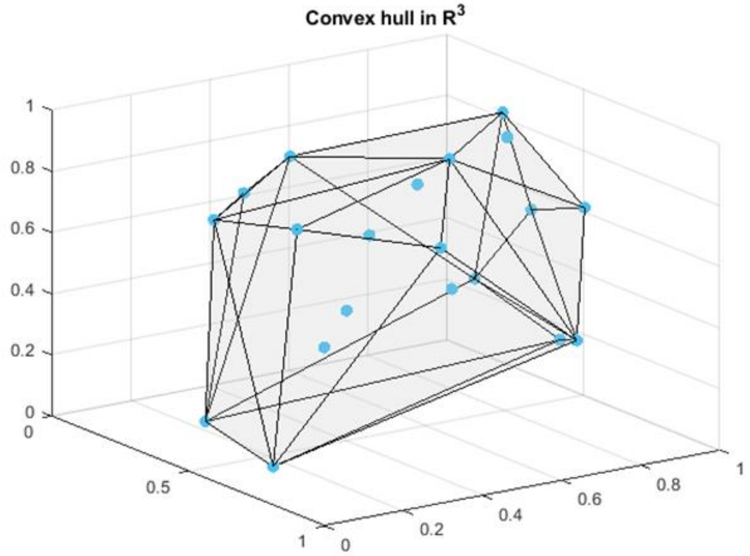
$$CH(X) = \left\{ \sum_{i=1}^{N} \alpha_i xi \| \sum_{i=1}^{N} \alpha_i = 1, 0 \leq \alpha_i \leq 1 \right\}$$

Based on One-class techniques

Anomaly detection based on One-class techniques

Implementation

- One-class techniques.
  - ACH.



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Based on One-class techniques

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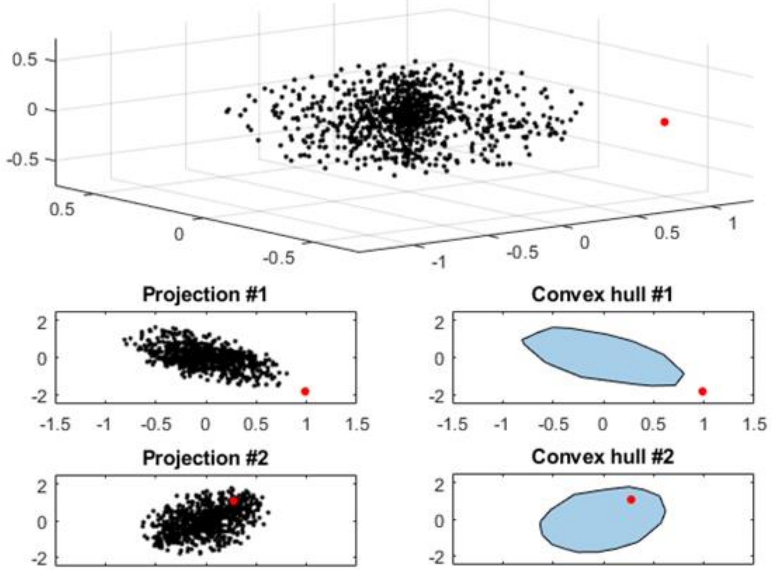

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Based on One-class techniques

Anomaly detection based on One-class techniques

Implementation

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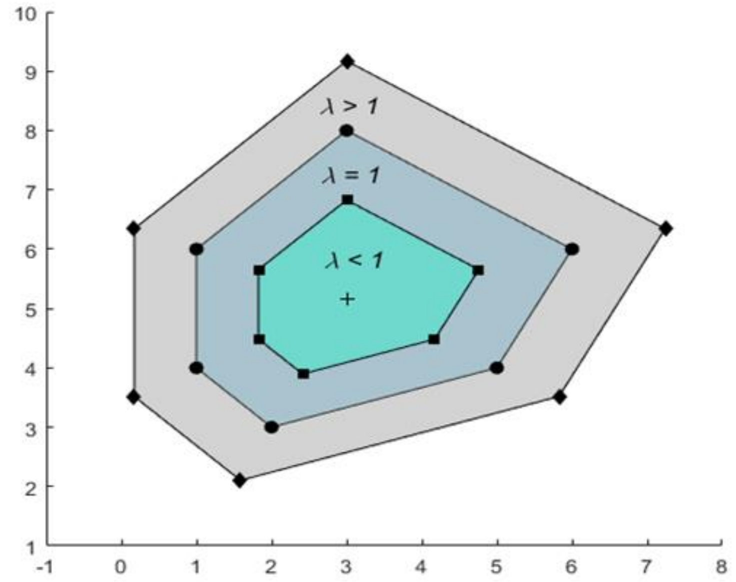


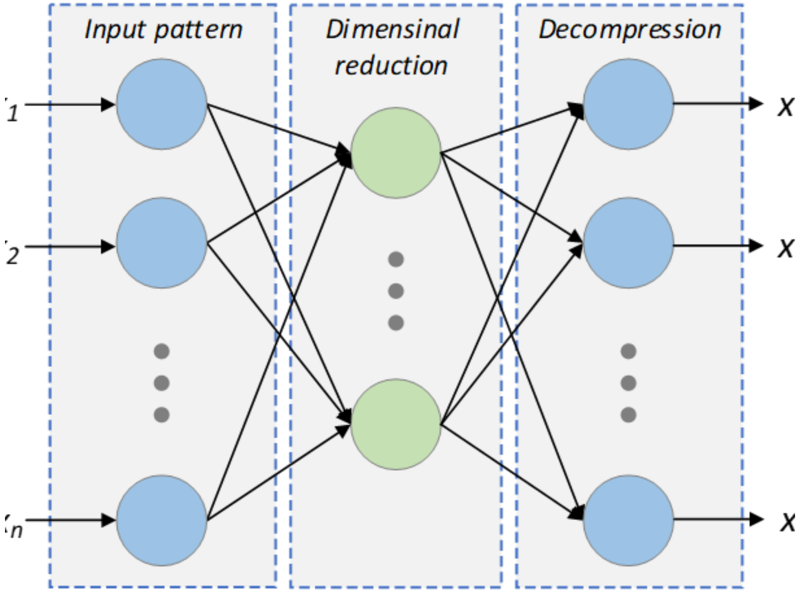
$$v^{\lambda} : \{\lambda v + (1 - \lambda)c \mid v \in CH(X)\}$$

Based on One-class techniques

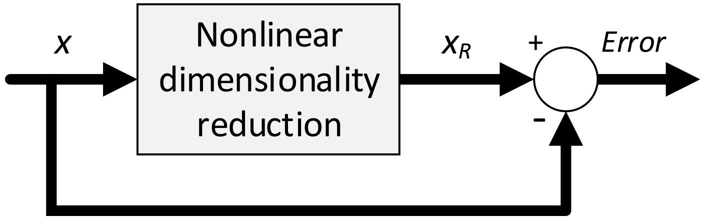
Anomaly detection based on One-class techniques

Implementation

- One-class techniques.
  - ACH.
  - **Autoencoder.**



$$v = f_1(W_1 x + b_1)$$
$$x_r = f_2(W_2 v + b_2)$$

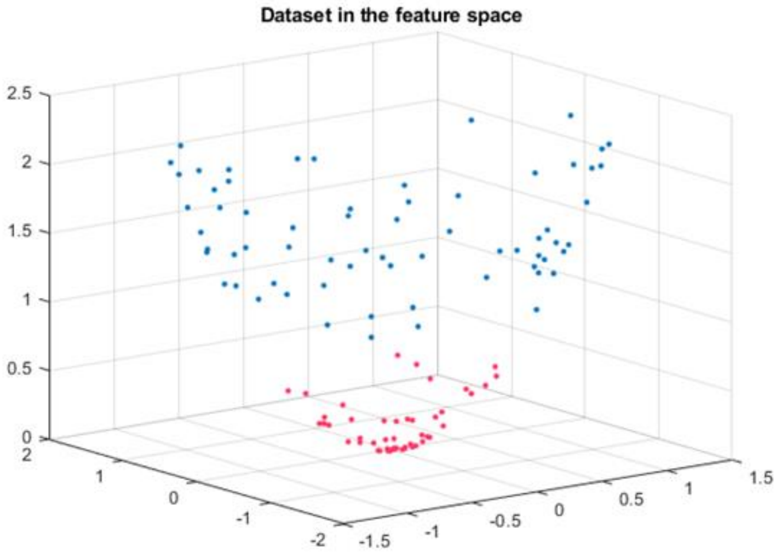


Based on One-class techniques

Anomaly detection based on One-class techniques

Implementation

- One-class techniques.
  - ACH.
  - Autoencoder.
  - **SVM.**



$$min\left(0.5||w||^2+\frac{1}{\nu l}\sum_{i=1}^{l}\xi_i-b\right)$$

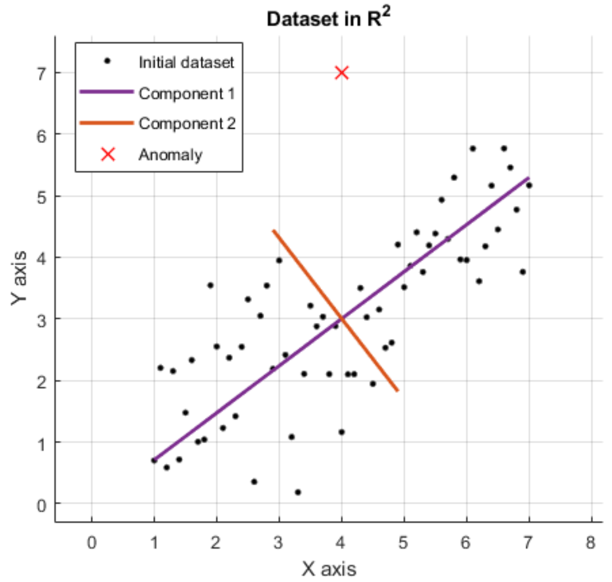
$$(w\cdot\delta(x_i))\geq b-\xi_i),\xi_i\geq 0$$

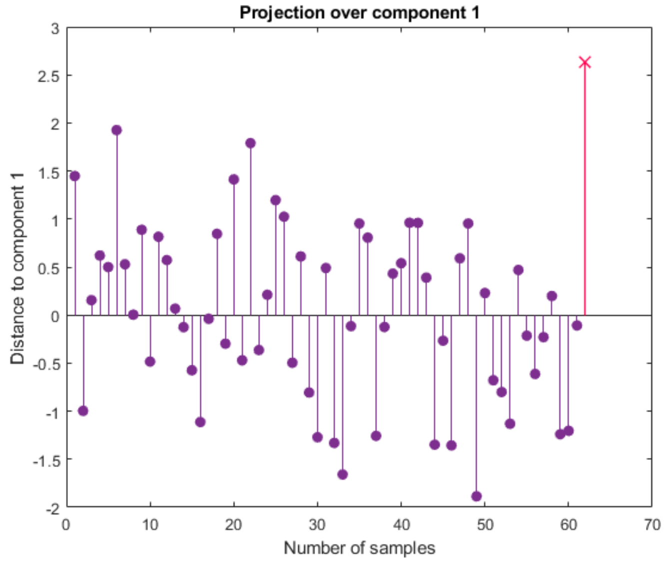
Based on One-class techniques

Anomaly detection based on One-class techniques

Implementation

- One-class techniques.
  - ACH.
  - Autoencoder.
  - SVM.
  - **PCA.**





$$min\left(0.5||w||^2+\frac{1}{\nu l}\sum_{i=1}^{l}\xi_i-b\right)$$

$$(w\cdot\delta(x_i))\geq b-\xi_i),\xi_i\geq 0$$

$$e(x)=||x-x_{pr}||$$

Based on One-class techniques

Anomaly detection based on One-class techniques

Implementation

- One-class techniques.
  - ACH.
  - Autoencoder.
  - SVM.
  - PCA.
- **Validation**

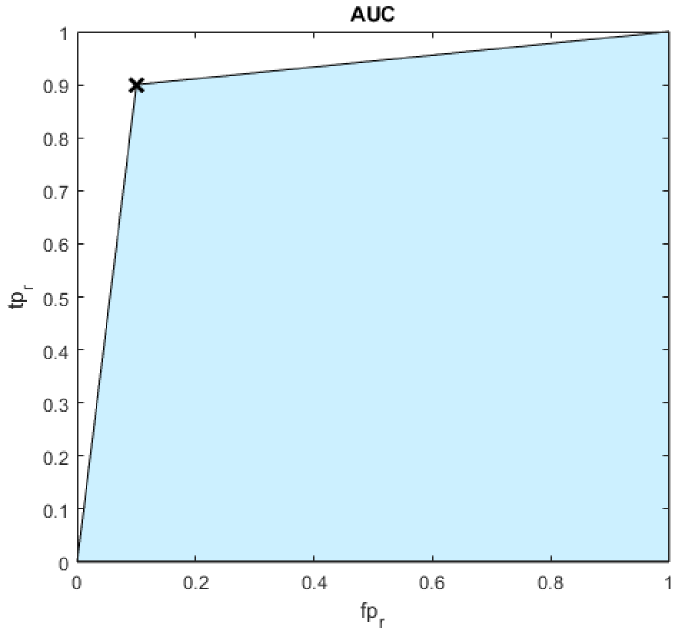
		Predicted class		
		Positive	Negative	
Real class	Positive	True Positives (TP)	False Negatives (FN)	$TP+FN=P$
	Negative	False Positives (FP)	True Negatives (TN)	$FP+TN=N$

Based on One-class techniques

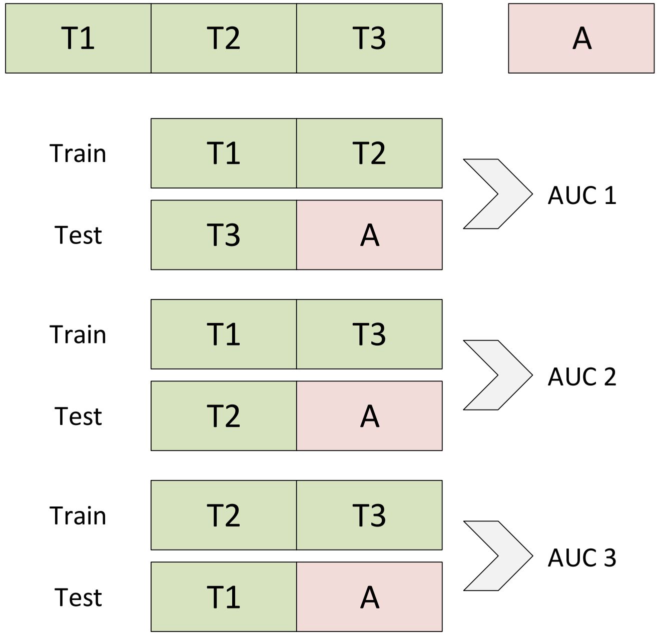
Anomaly detection based on One-class techniques

Implementation

- One-class techniques.
  - ACH.
  - Autoencoder.
  - SVM.
  - PCA.
- **Validation**



Tpr – True positive rate
Fpr – False positive rate

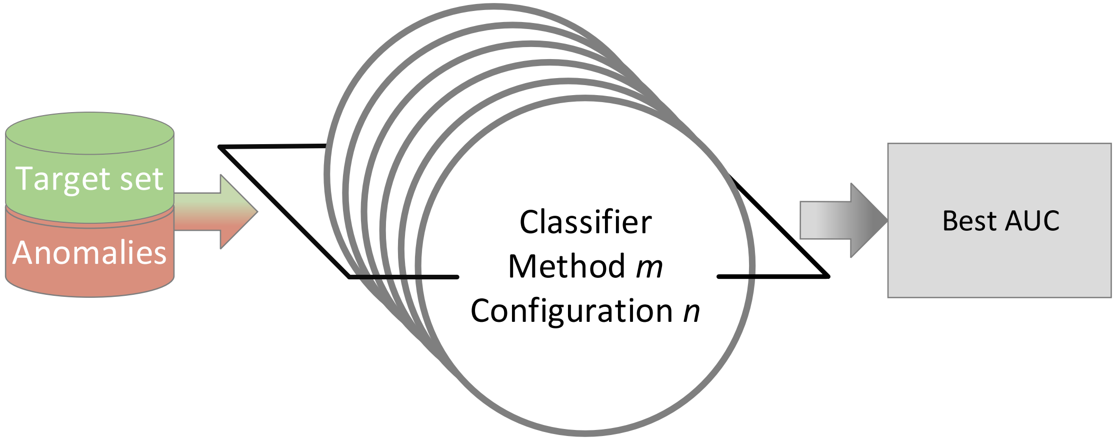


Based on One-class techniques

Anomaly detection based on One-class techniques

Implementation

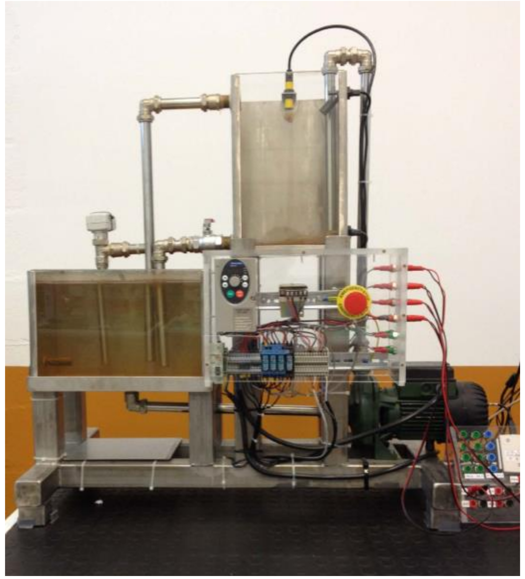
- One-class techniques.
  - ACH.
  - Autoencoder.
  - SVM.
  - PCA.
- Validation
- **Best Configuration**

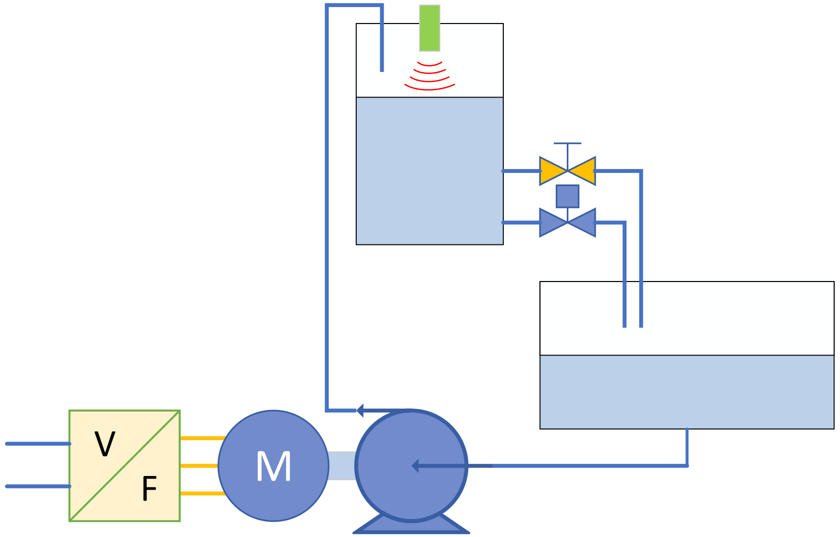


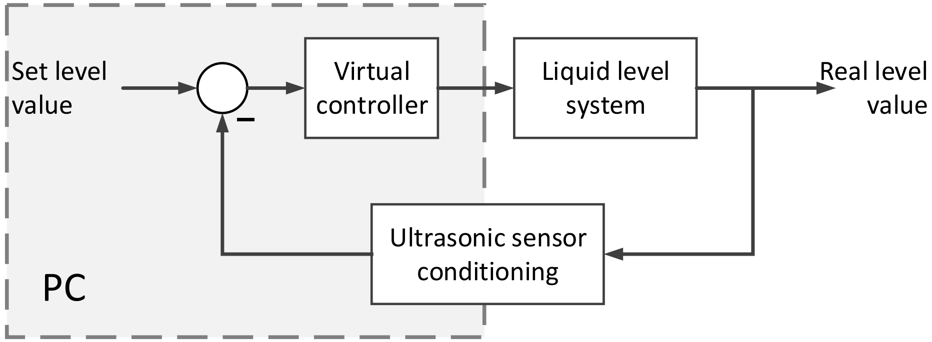
Based on One-class techniques

Anomaly detection based on One-class techniques

Anomaly detection based on one-class intelligent techniques over a control level plant → Real case of application







Monitored variables.

- Control signal.
- Error signal.
- Plant coefficients.
- Set point.
- Process value.

Based on One-class techniques

Anomaly detection based on One-class techniques

Dataset

- Target set: electric valve closed: 5400 samples.
- Anomalies.
  - Electric valve open 10 %: 5400 samples.
  - Electric valve open 30 %: 5400 samples.
  - Electric valve open 50 %: 5400 samples.
  - Electric valve open 70 %: 5400 samples.
  - Electric valve open 90 %: 5400 samples.

Based on One-class techniques

Anomaly detection based on One-class techniques

Experiments and results.

- Classifier inputs.
  - Control signal.
  - Error.
  - Plant coefficients.
- Data conditioning.
  - 0 to 1.
  - Z-Score.
- ACH.
  - Expansion parameter λ: 0.9, 1, 1.1.
  - Projections: 5, 10, 50, 100, 500, 1000.
- Autoencoder.
  - Neurons in the hidden layer: 1:1:4.
- SVM.
  - Outlier percentage: 0:1:10.
  - Kernel function: Gaussian.
- Tested anomalies. Valve open (%):
  - 10:20:90.

Based on One-class techniques

Anomaly detection based on One-class techniques

Experiments and results.

Projections	λ	AUC	Training time (min)
1000	1,1	99,78	13,25

Hidden layer neurons	Conditioning	AUC	Training time (min)
4	Z-Score	99,49	8,83

Outlier percentage	Conditioning	AUC	Training time (min)
5	0-1	99,35	1,04

Conclusions and future work

Conclusions and future works

- Anomaly and fault detection are very important in general terms
- Explain the anomaly or fault could be complex, but very useful
- Fault-Tolerant Systems are a challenge
- These techniques could have application in some different fields (i.e., traceability, quality assurance, operational control, …)
- Future works:
    - The real time implementation of systems that have a very high computational cost, like vision-based ones.
    - To apply these techniques over day a day common people problems, like water management

Thank you

Intelligent systems for anomaly detection of real cases for production optimizing

José Luis Calvo Rolle

Grupo de Investigación Ciencia y Técnica Cibernética
UNIVERSIDADE DA CORUÑA

UNED 2025 - Madrid