Challenges in RAM&PHM

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PHM: Market Opportunity

Energy Industry

•<u>Nuclear Power Plants</u>:
Operation and maintenance cost = 60%- 70% of the total cost of production[1]

•<u>Wind Farms:</u>
Maintenance costs =1.5% - 2% per year of the original turbine investment[2]

Mining Industry

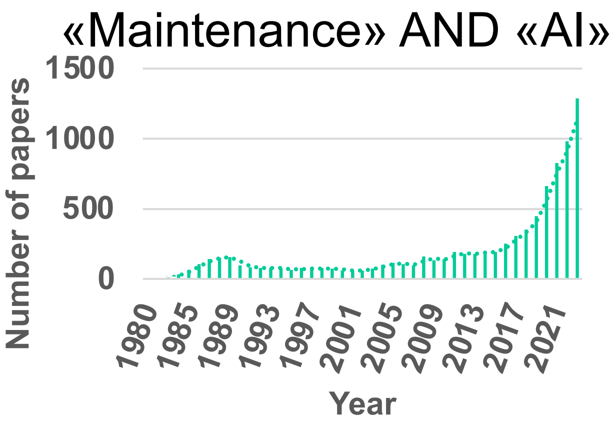
Maintenance cost > 30% of the total cost of production[3]

[1]R.M. Ayo-Imoru, A.C. Cilliers, "*A survey of the state of condition-based maintenance (CBM) in the nuclear power industry"*, Annals of Nuclear Energy", 2018.

[2]Danish Wind industry Association, (http://xn--drmstrre-64ad.dk/wp-content/wind/miller/windpower%20web/en/tour/econ/oandm.htm)

[3]Komljenovic D, Paraszczak J, Kecojevic V. *Potential for improvement of reliability and maintenance in mining operations based on nuclear industry know-how and experience*. In: Mine Planning and Equipment Selection 2005; 2005. p. 143–52.

PHM: Market Opportunity



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AI-based PHM Model

[1]R.M. Ayo-Imoru, A.C. Cilliers, "*A survey of the state of condition-based maintenance (CBM) in the nuclear power industry"*, Annals of Nuclear Energy", 2018.

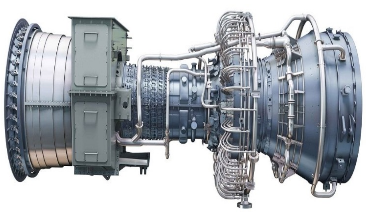
[2]Danish Wind industry Association, (http://xn--drmstrre-64ad.dk/wp-content/wind/miller/windpower%20web/en/tour/econ/oandm.htm)

[3]Komljenovic D, Paraszczak J, Kecojevic V. *Potential for improvement of reliability and maintenance in mining operations based on nuclear industry know-how and experience*. In: Mine Planning and Equipment Selection 2005; 2005. p. 143–52.

PHM: The Challenge

Is my PHM model a magician?

I don't believe it!



AI-based PHM Model

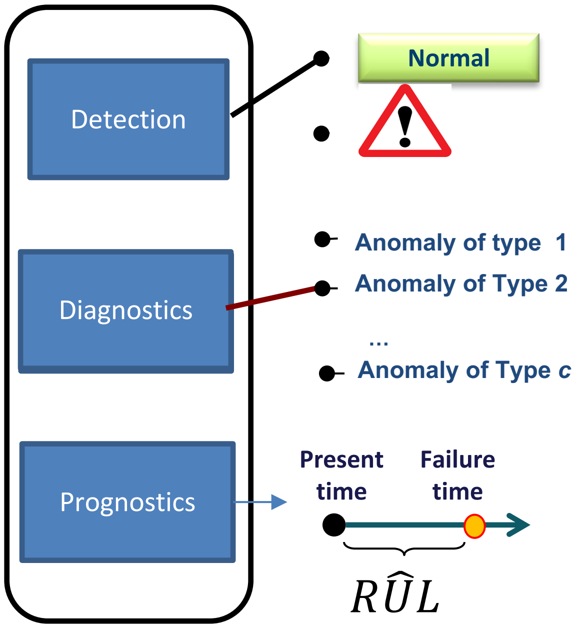
It is degraded due to creeping

It is going to fail in: 57:25:18

Trustworthy=

1) **Accurate**
2) **Confident**
3) **Consistent with physics**
4) **Explainable**

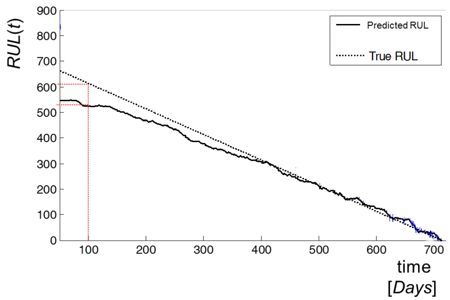
PHM: Accuracy



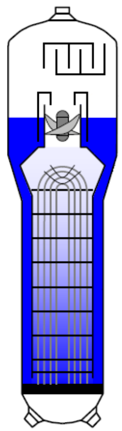
- ❑ Few False Alarms
- ❑ Few Missing Alarms

- ❑ Large Classification Accuracy (for each anomaly type)

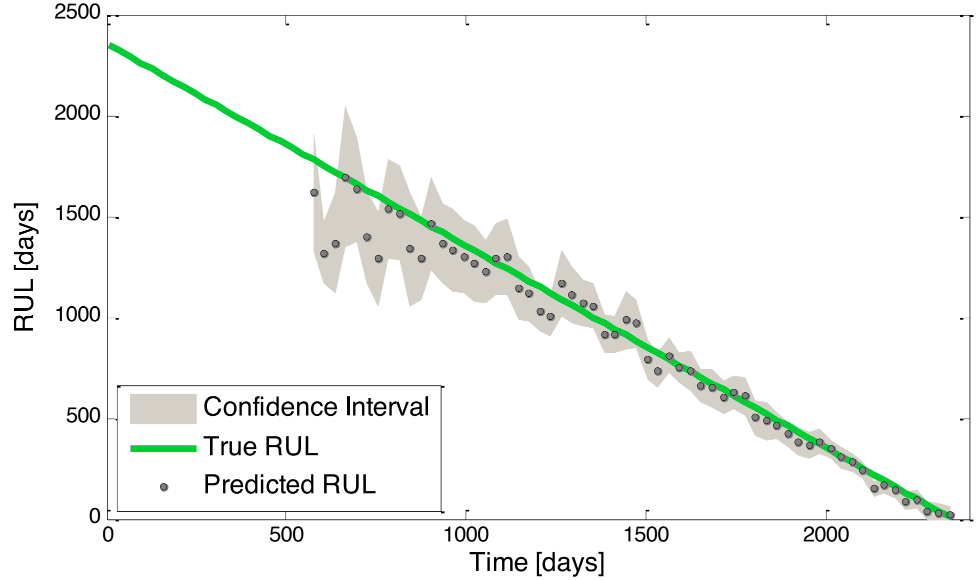
- ❑ $\hat{RUL} \cong RUL$



PHM: Confidence



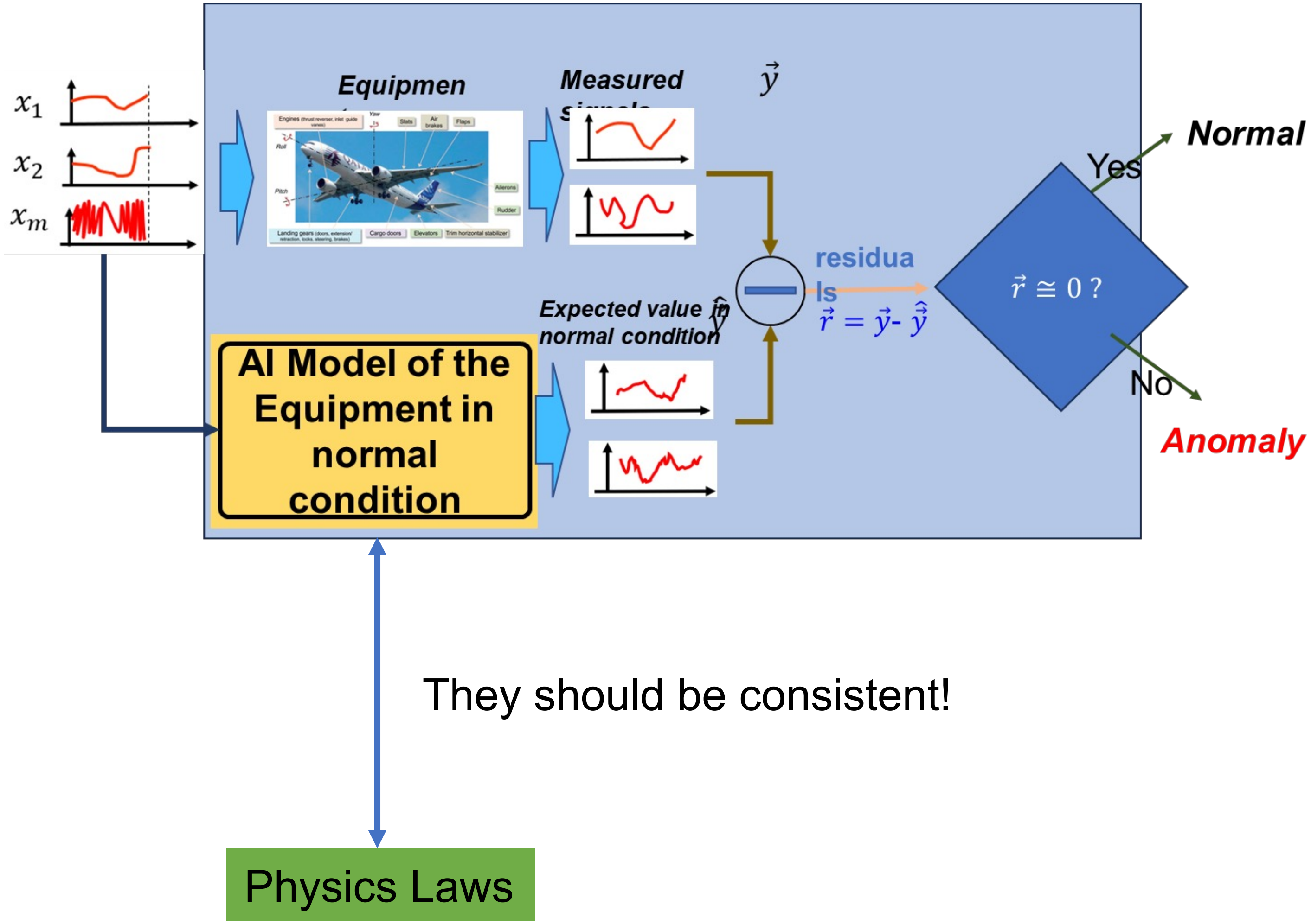
Prognostic Model



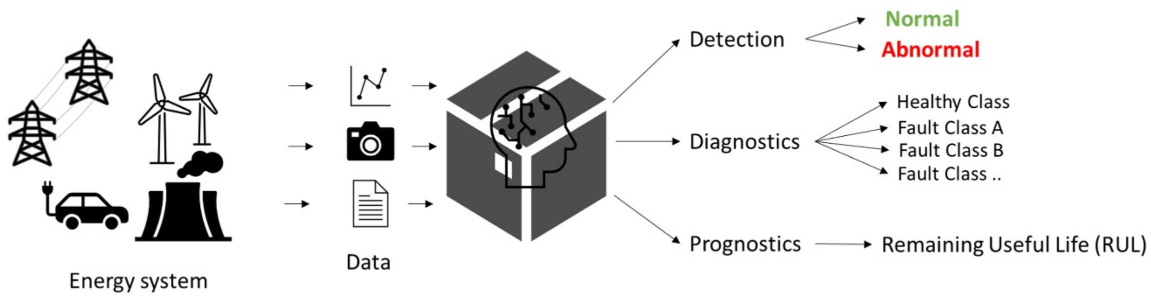
Confidence Interval:

- As small as possible
- Good Coverage

PHM: Consistency with Physics



PHM: Explainability



Disclose the internal working of the model

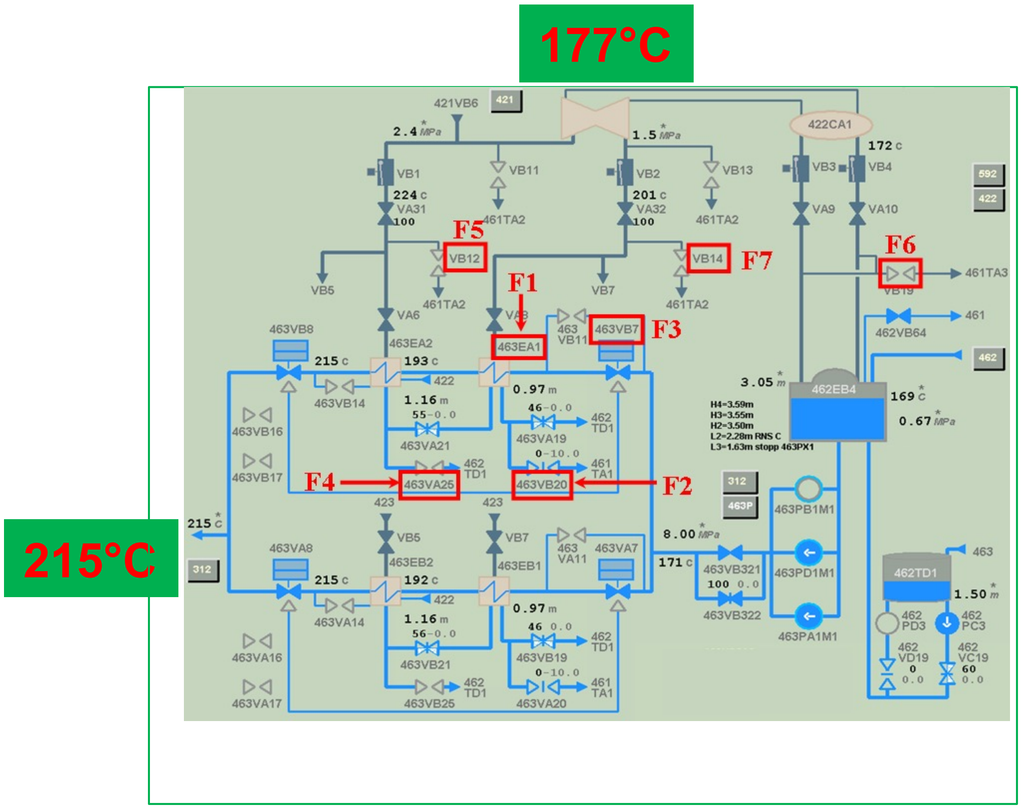
Unveil the causes behind the AI model outcomes

Industrial Systems:
- Some Characteristics

Prognostics and Health Management:
  - Fault Detection
  - Fault Diagnostics
  - Fault Prognostics
- Decision Making

Conclusions

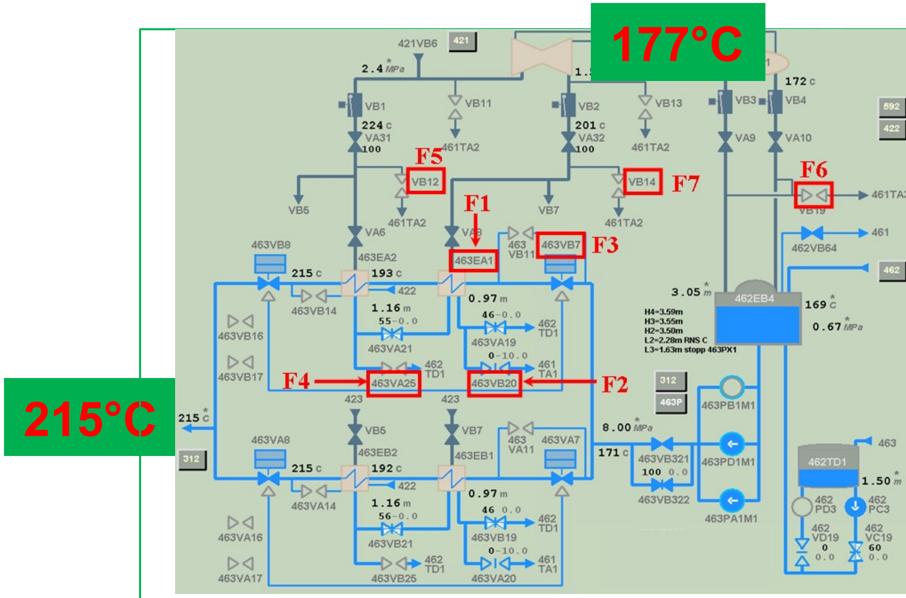
Industrial systems: hundreds of highly interconnected components



Industrial Systems - Some Characteristics

Industrial systems: hundreds of highly interconnected components

- **Big data:**
  - **Hundreds of signals**

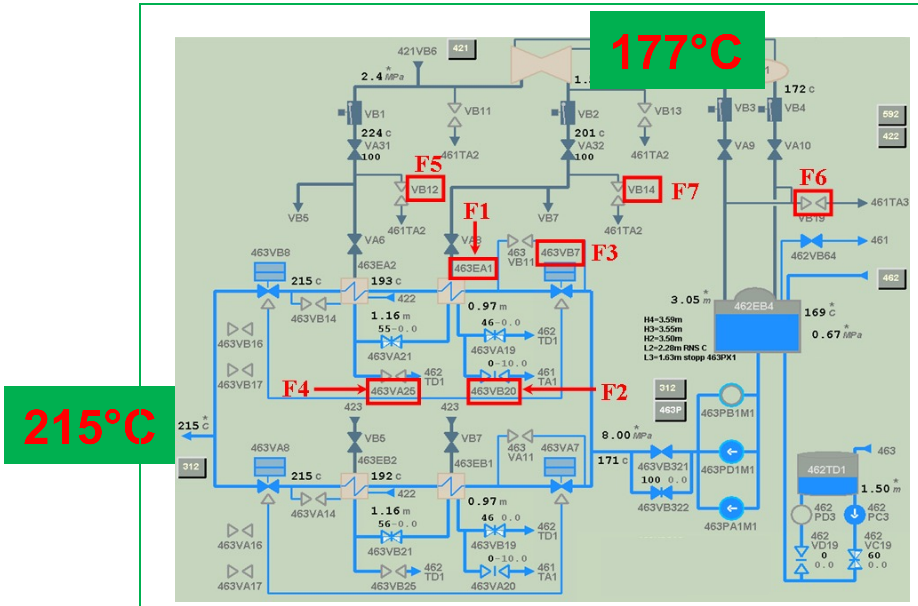


*Hundreds of signals

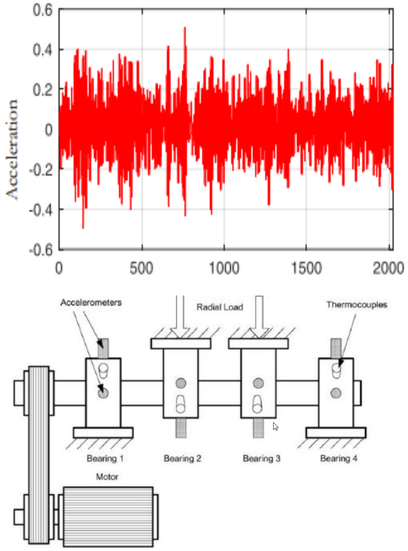
*Zio E., Baraldi P., Pedroni N.; "*Selecting features for nuclear transients classification by means of genetic algorithms»;* (2006) IEEE Transactions on Nuclear Science, 53 (3), pp. 1479 - 1493.

Industrial systems: hundreds of highly interconnected components

- **Big data:**
  - Hundreds of signals
  - **Signals measured at high frequency**



*Hundreds of signals

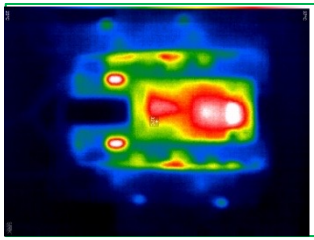


*Vibration signals at high frequency (up to 25kHz)

*Baraldi P., Cannarile F., Di Maio F., Zio E., «*Hierarchical k-nearest neighbours classification and binary differential evolution for fault diagnostics of automotive bearings operating under variable conditions*»; (2016) Engineering Applications of Artificial Intelligence, 56.

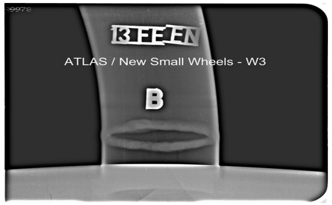
Industrial systems: hundreds of highly interconnected components

- **Big data:**
  - Hundreds of signals
  - Signals measured at high frequency
  - **Images**



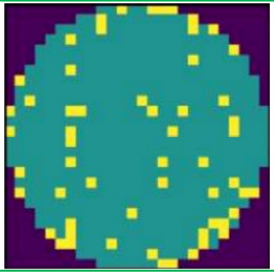

Inverter of a FEV

iReλ 4.0 intelligent Reliability 4.0



Weld in pipelines

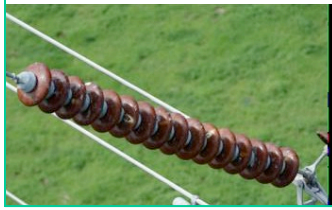
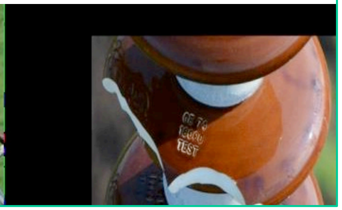
CERN



Wafer maps in the Semiconductor industry

iReλ 4.0 intelligent Reliability 4.0

Power line insulators

*Yang Z., Baraldi P., Zio E.; «*A multi-branch deep neural network model for failure prognostics based on multimodal data*»; (2021) Journal of Manufacturing Systems, 59, pp. 42 – 50.

Industrial systems: hundreds of highly interconnected components

- **Big data:**
  - Hundreds of signals
  - Signals measured at high frequency
  - Images
  - Texts

bucket

adaptor

RAISED_DATE	Original.Shorttext
19/7/2009	Replace bucket goanna bars.
30/9/2009	Repairs to bucket both outside ad
04/10/2009	c /o pos1 tooth and pin

Détail signalement
During Instrumentation of Loco found fully rusting (Oxidis ed foreign materials)on CT Busbar and oily on VCB. 1. Pot ential Transformer need to replace of Section-A. 2. Sparkin g spots found in Lightning Aresster of Section-A. # #

RECET4Rail

Case description	Consequence
At 16:00 pm the oil level has risen in the separation vessel, which led the oil to pass through with the gas to … some valves were not directly connected to the drainage system which led to the oil to spill in the surrounding Area	Fire/Explosion

Z. Yang, P. Baraldi, E. Zio, "*A novel method for maintenance record clustering and its application to a case study of maintenance optimization*"; (2020) Reliability Engineering and System Safety, Vol. 203.
D. Valcamonico, P. Baraldi, E. Zio, L. Decarli, A. Crivellari, L. Rosa, *«Combining natural language processing and bayesian networks for the probabilistic estimation of the severity of process safety events in hydrocarbon production assets;* (2024) Reliability Engineering and System Safety, Vol. 241(C).

Industrial Systems - Some Characteristics

Industrial systems: hundreds of highly interconnected components

- **Big data → Big Knowledge Information and Data (KID)**

KID
- Hundreds of signals
- Signals measured at high frequency
- Images
- Texts

RAISED_DATE	Original.Shorttext
19/7/2009	Replace bucket goanna bars.
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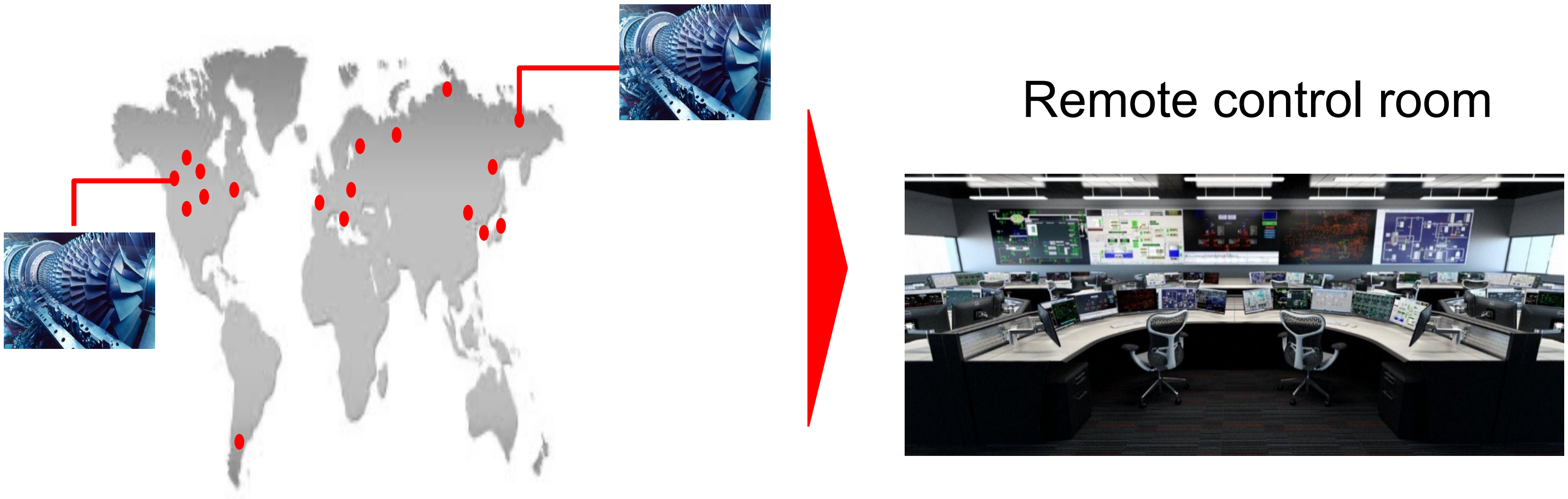
Industrial Systems - Some Characteristics

Industrial systems:

- Big KID
- **Fleet of systems**

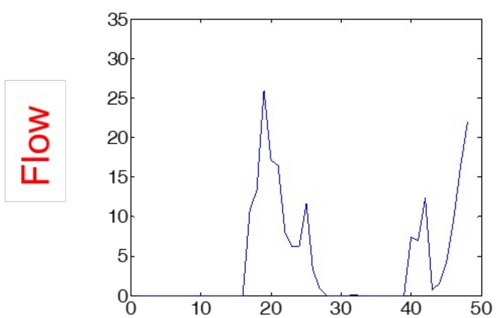


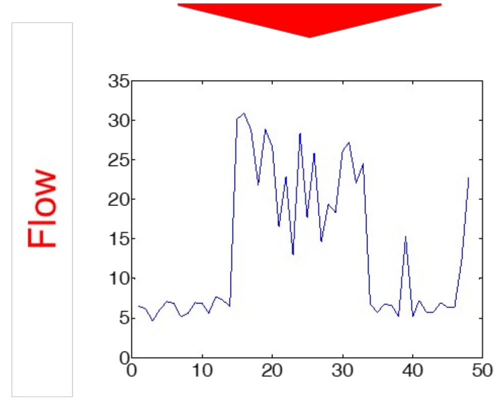
Al-Dahidi S., Di Maio F., Baraldi P., Zio E., Seraoui R.; «*A framework for reconciliating data clusters from a fleet of nuclear power plants turbines for fault diagnosis*»; (2018) Applied Soft Computing Journal, 69, pp. 213 – 231.

Industrial Systems - Some Characteristics

Industrial systems:

- Big KID
- Fleet of systems **in different environmental and operating conditions**

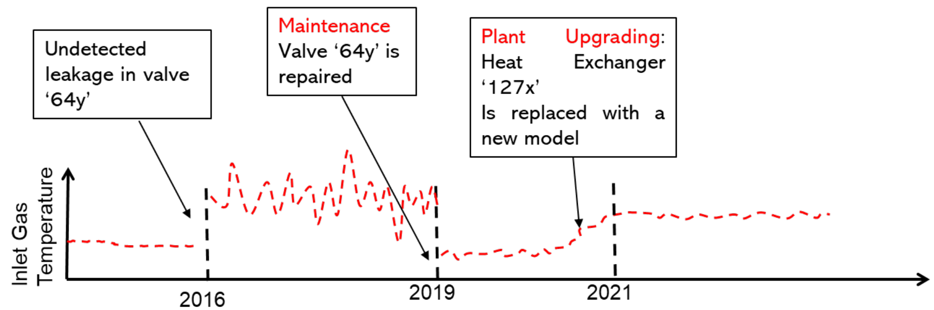


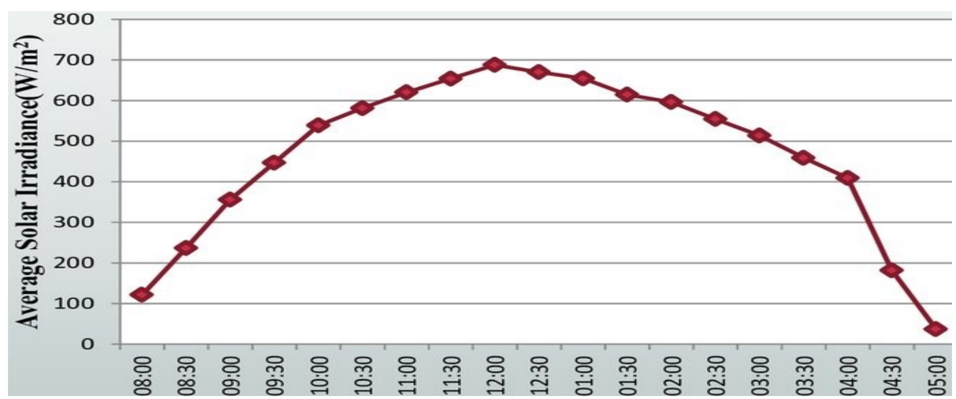


Al-Dahidi S., Di Maio F., Baraldi P., Zio E.; «*Remaining useful life estimation in heterogeneous fleets working under variable operating conditions*»; (2016) Reliability Engineering and System Safety, 156, pp. 109-124.

Industrial systems:

- Big KID
- Fleet of systems in different environmental and operating conditions
- **Evolving environment**





Yang Z., Al-Dahidi S., Baraldi P., Zio E., Montelatici L.; "*A Novel Concept Drift Detection Method for Incremental Learning in Nonstationary Environments*"; (2020) IEEE Transactions on Neural Networks and Learning Systems, 31 (1).

Industrial Systems:

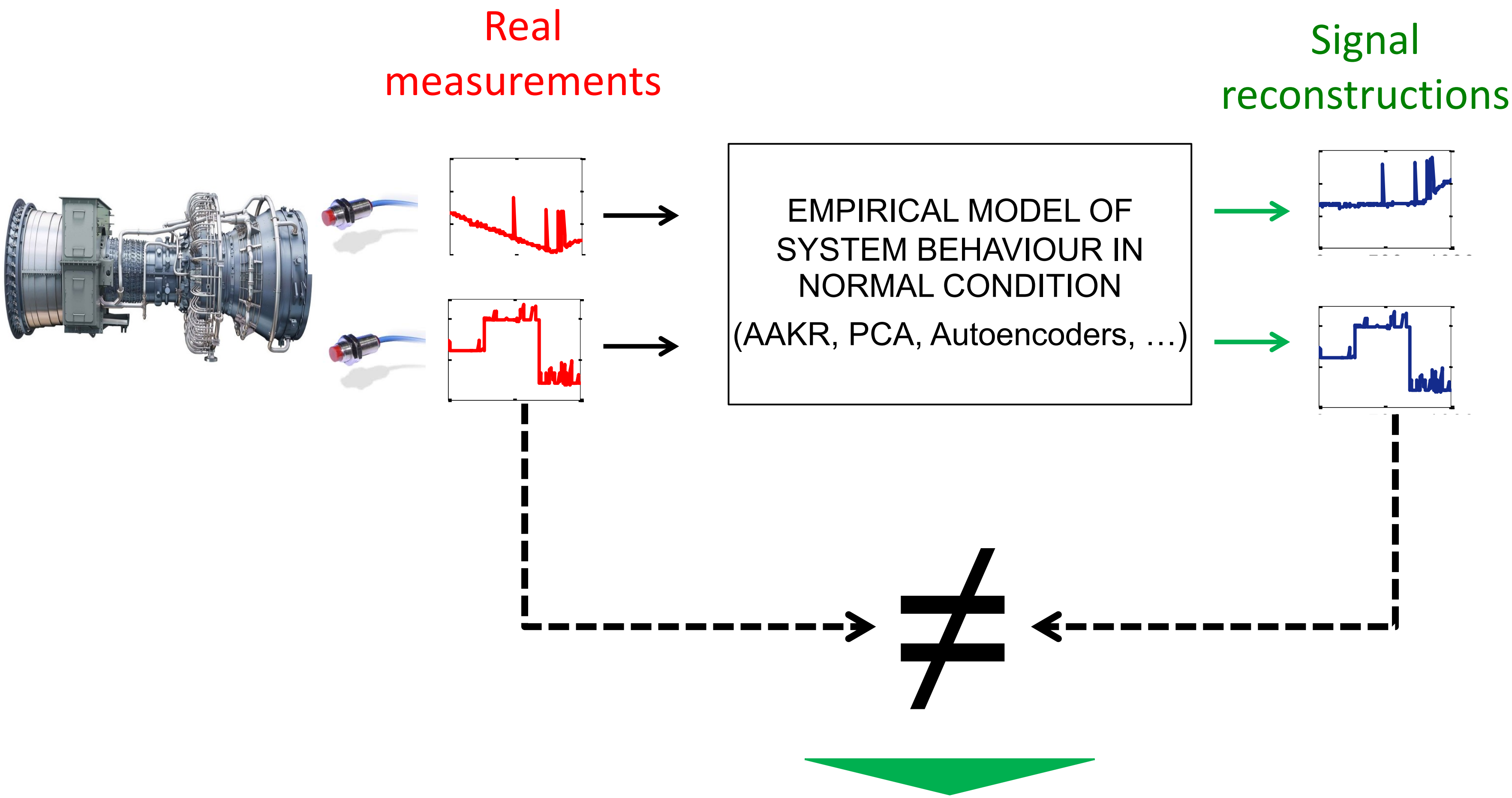
- **Some Characteristics**

PHM:

  - **Fault Detection**
  - **Fault Diagnostics**
  - **Fault Prognostics**

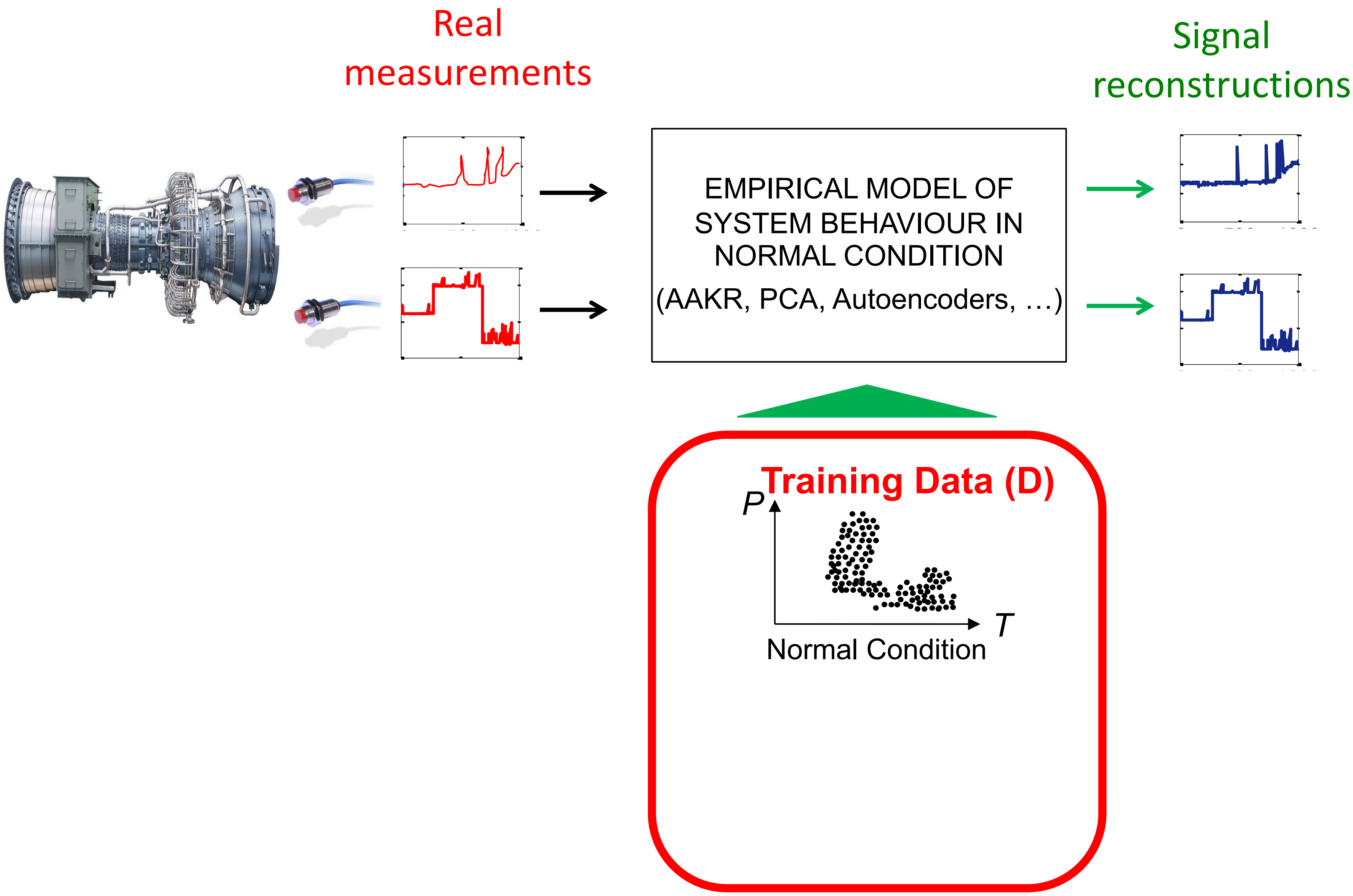
Conclusions

Fault Detection: Method



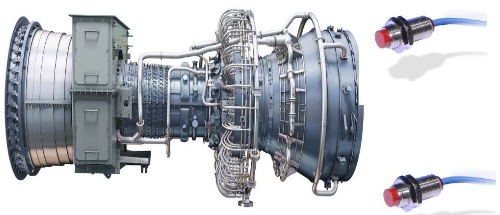
Abnormal Condition

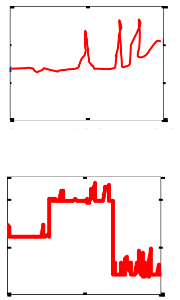
Fault Detection: Data (D)



Fault Detection: Knowledge and Data - K(I)D

Real measurements

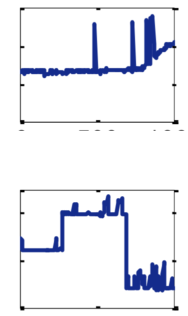




MODEL OF SYSTEM BEHAVIOUR IN NORMAL CONDITION

(AAKR, PCA, Autoencoders, …)

Signal reconstructions



Training Data (D)

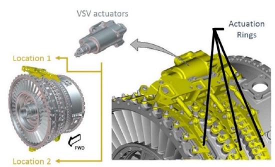
Normal Condition

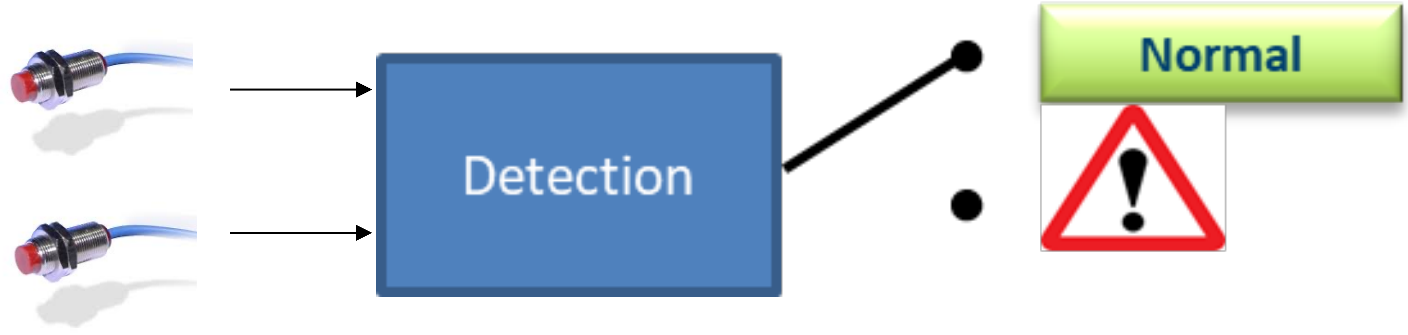
Knowledge (K)

Physics-based models of the system

$$\frac{dx}{dt} = A\exp\left(-\frac{Q}{RT}\right)\phi^{n}$$

Electro-Hydraulic Servo-Actuators (EHSA):





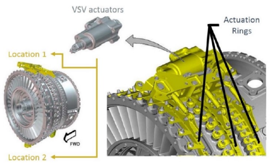
Relevance:

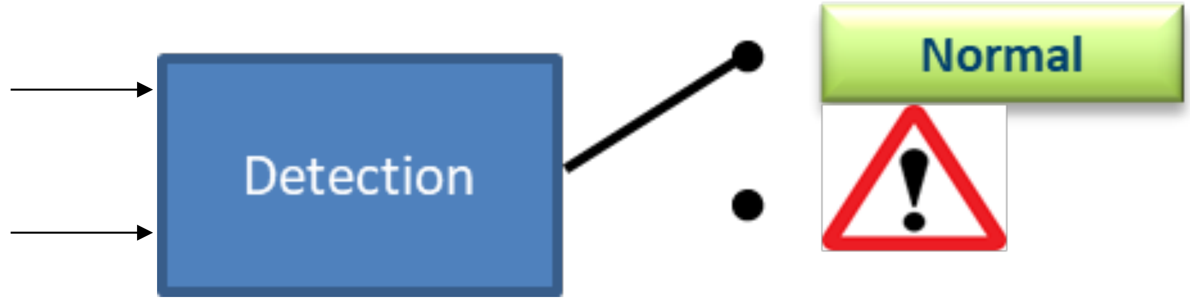
- Safety-critical system:
  - ➢ failure → engine stall

C. Lai, P. Baraldi, E. Zio, "*Physics-Informed deep Autoencoder for fault detection in New-Design systems*",(2024), Mechanical Systems and Signal Processing, 215.

Example: Data (D)

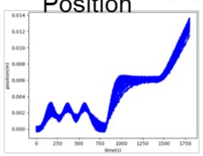
Electro-Hydraulic Servo-Actuators (EHSA):





Data (D)

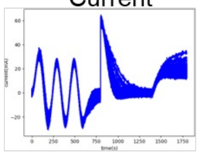
Position



Pre-flight test

+

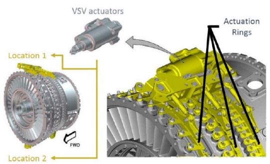
Current



Pre-flight test

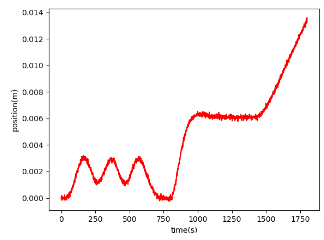
Example: Empirical Model - AutoEncoder (D)

Electro-Hydraulic Servo-Actuators (EHSA):

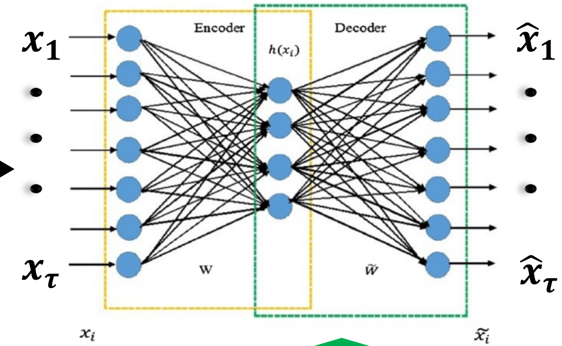


Real measurements

Position

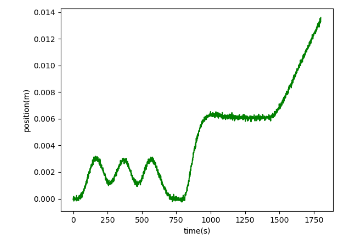


AutoEncoder (AE)



Signal reconstructions

Position

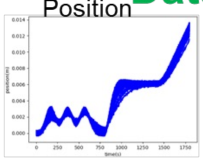


Pre-flight test

TRAINING

Data (D)

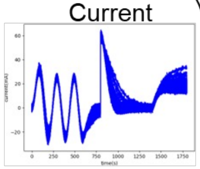
Position



Pre-flight test

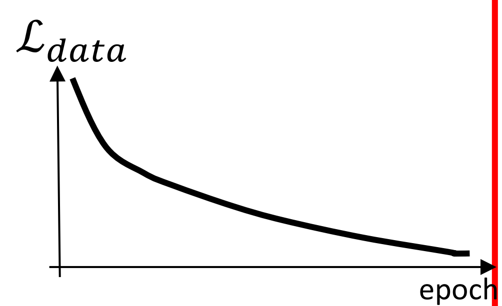
+

Current



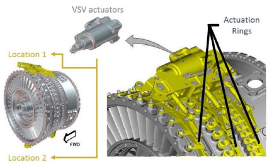
Pre-flight test

$$\mathcal{L}_{data} = \sum_{\substack{normal\\condition\\data}} (x_t - \hat{x}_t)^2$$



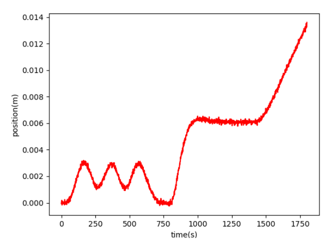
Example: Knowledge (K)

Electro-Hydraulic Servo-Actuators (EHSA):

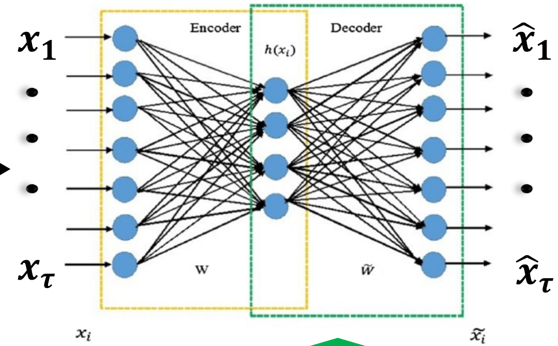


Real measurements

Position

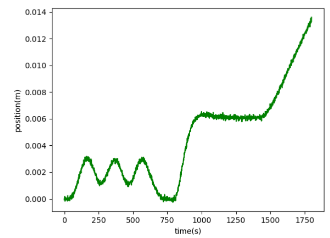


AutoEncoder (AE)



Signal reconstructions

Position

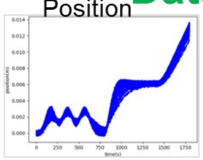


Pre-flight test

TRAINING

Data (D)

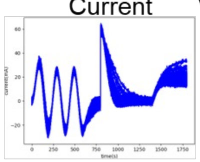
Position



Pre-flight test

+

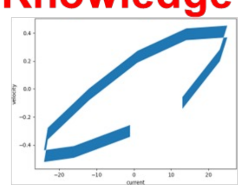
Current



Pre-flight test

Knowledge (K)

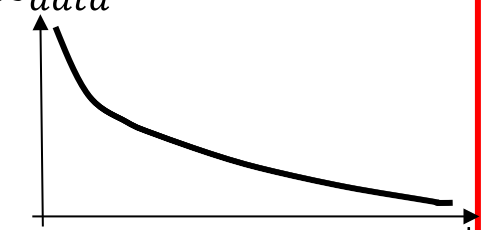
Velocity



Healthy region

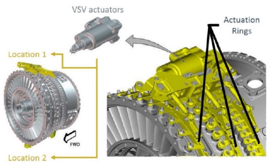
Current

$$\mathcal{L}_{data} = \sum_{\substack{normal\\condition\\data}} (x_t - \hat{x}_t)^2$$



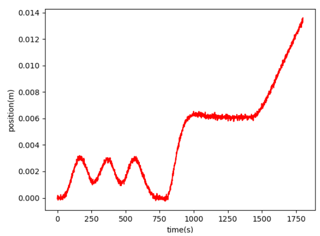
Example: Physics-Informed AE (KD)

Electro-Hydraulic Servo-Actuators (EHSA):

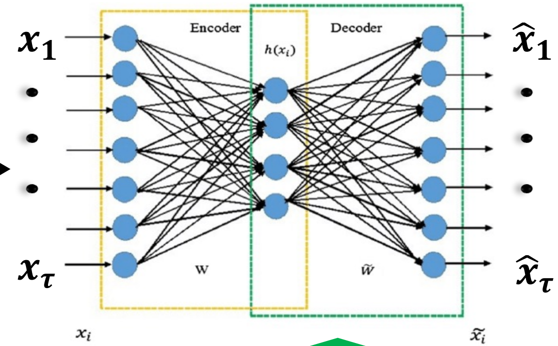


Real measurements

Position

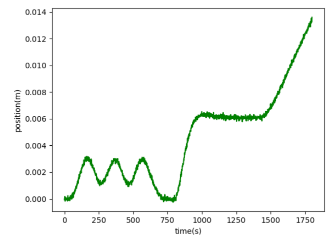


Physics-Informed AE



Signal reconstructions

Position

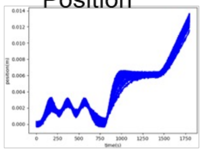


Pre-flight test

TRAINING

Data (D)

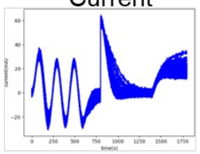
Position



Pre-flight test

\+

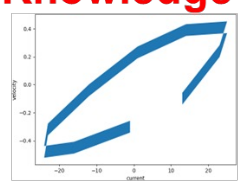
Current



Pre-flight test

Knowledge (K)

Velocity



Healthy region

Current

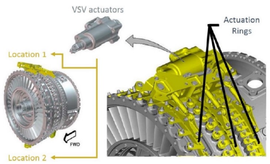
Loss Function $= \overset{(D)}{\mathcal{L}_{data}} + \overset{(K)}{\mathcal{L}_{phy}}$

$$\mathcal{L}_{data} = \sum_{\substack{training\\data}} (x_t - \hat{x}_t)^2$$

$$\mathcal{L}_{phy} = \sum_{\substack{training\\data}} Meas(\hat{x}_t \text{ in Disagreement with knowledge})$$

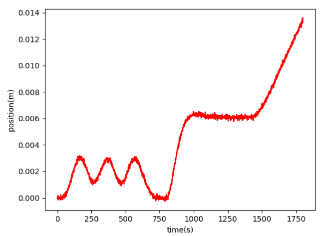
Example: Physics-Informed AE (KD)

Electro-Hydraulic Servo-Actuators (EHSA):

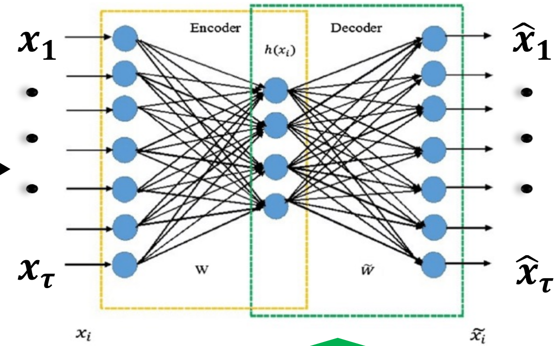


Real measurements

Position

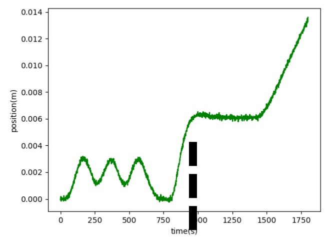


Physics-Informed AE



Signal reconstructions

Position



Pre-flight test

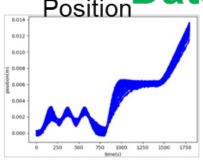
TRAINING

Loss Function $= \mathcal{L}_{data}^{(D)} + \mathcal{L}_{phy}^{(K)}$

$\frac{d\hat{x}}{dt}$

Data (D)

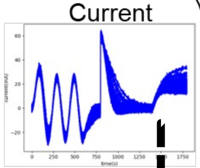
Position



Pre-flight test

+

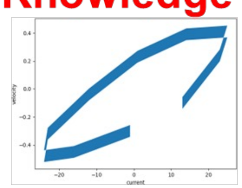
Current



Pre-flight test

Knowledge (K)

Velocity



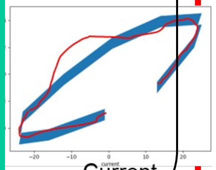
Healthy region

Current

$$\mathcal{L}_{data} = \sum_{\substack{training\\data}} (x_t - \hat{x}_t)^2$$

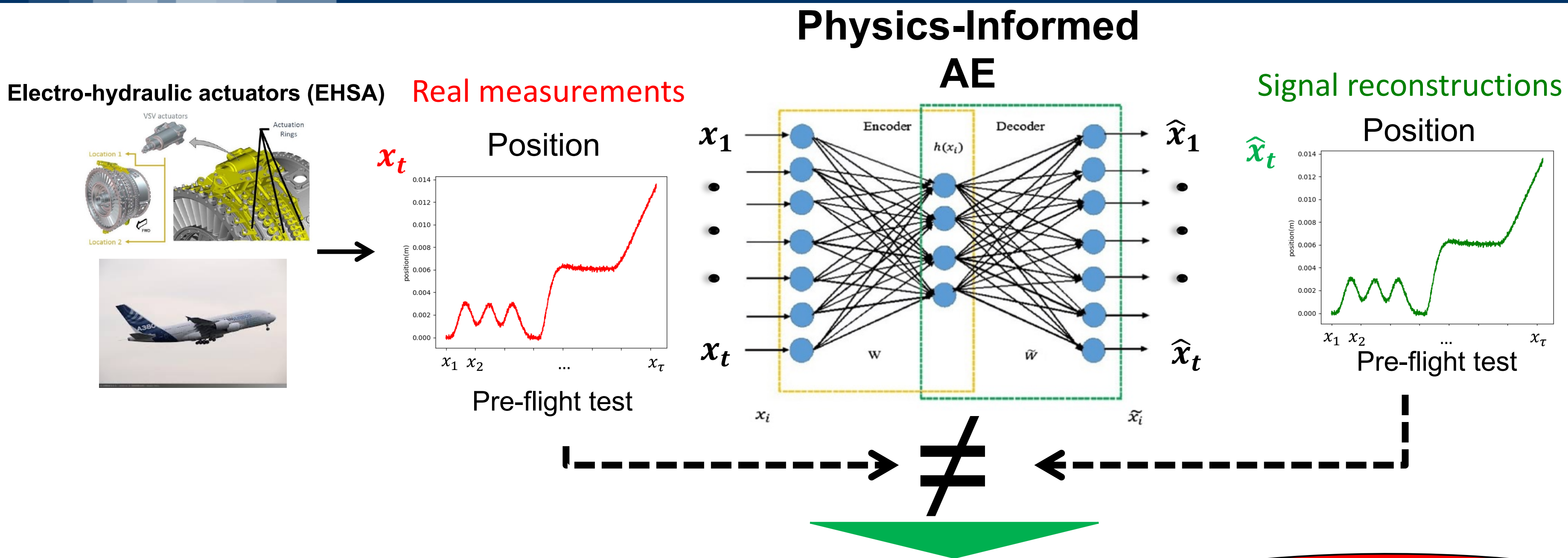
$$\mathcal{L}_{phy} = \sum_{\substack{training\\data}} Points \notin Region_{healthy}$$

velocity



Current

Example: Results



PHYSICS-INFORMED AE (TRADITIONAL AE)

GROUNDTRUTH

	Normal Condition	Abnormal Condition
Normal Condition	99,50% (99.38%)	0.40% (0,64%)
Abnormal Condition	0.50% (0.62%)	99,60% (99,36%)

Missed alarm rate

False alarm rate

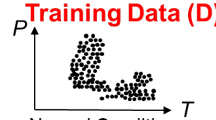
Example: Trustworthyness

Trustworthy Fault Detectiom

Accurate	Consistent with Laws of Physics	Confident	Providing an Explanation of the Prediction

Physics-Informed AE

Training Data (D)



Normal Condition

Knowledge (K)

Physics-based models of the system

$$\frac{dx}{dt} = A\exp\left(-\frac{Q}{RT}\right)\phi^n$$

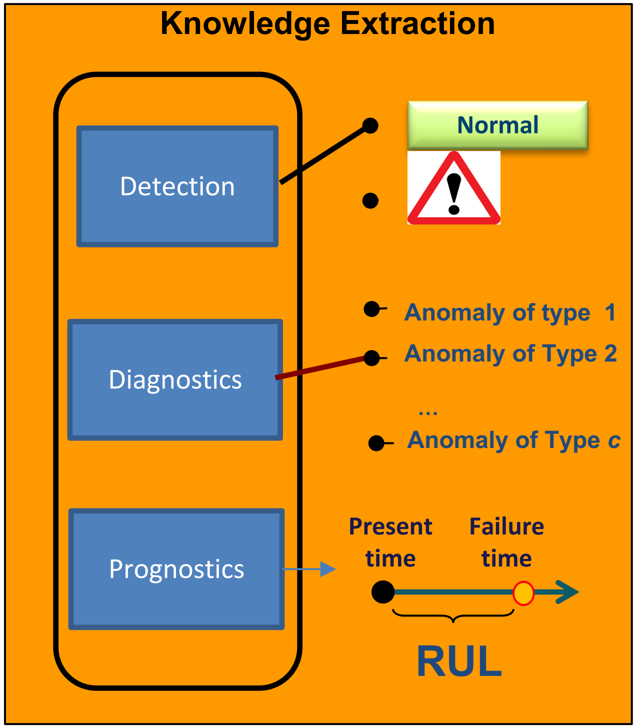
Industrial Systems:

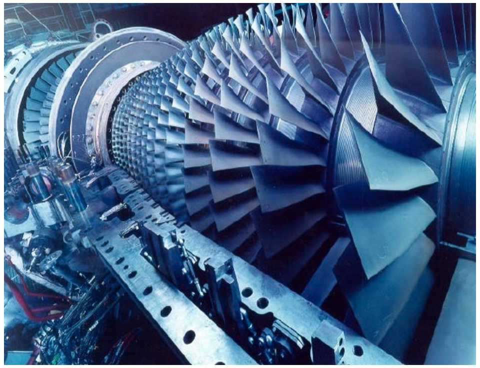
- Some Characteristics

Predictive Maintenance:

- Fault Detection
- Fault Diagnostics
- Fault Prognostics

Conclusions

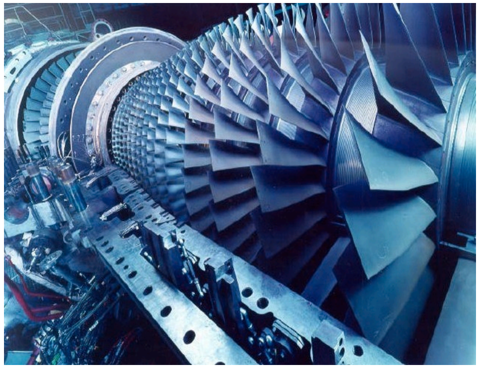




…

Empirical Classifier
(kNN, SVM, NN,…)

- C_0 = «Normal»
- C_1 = «Anomaly of Type 1»
- C_2 = «Anomaly of Type 2»



Empirical Classifier

(kNN, SVM, NN,…)

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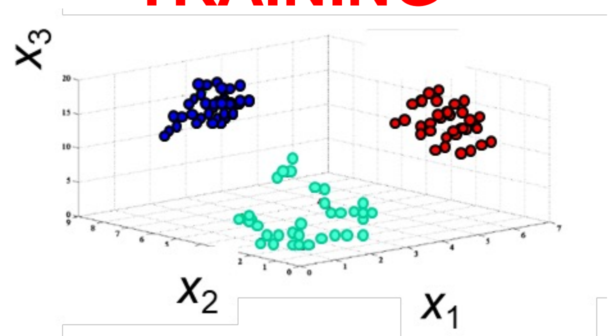
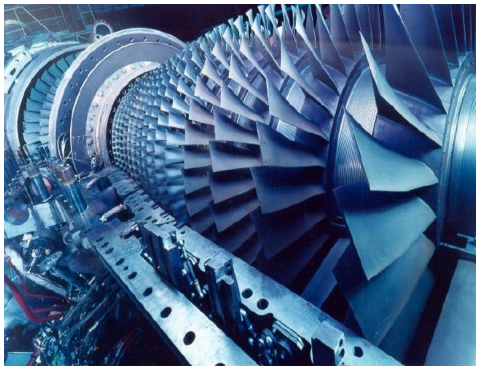
TRAINING



Real data «x_1,x_2,…x_n, class»



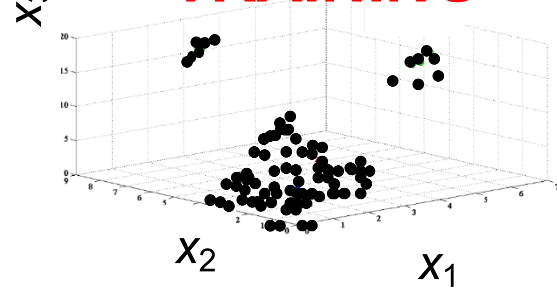
...

Empirical Classifier

(kNN, SVM, ANN,…)

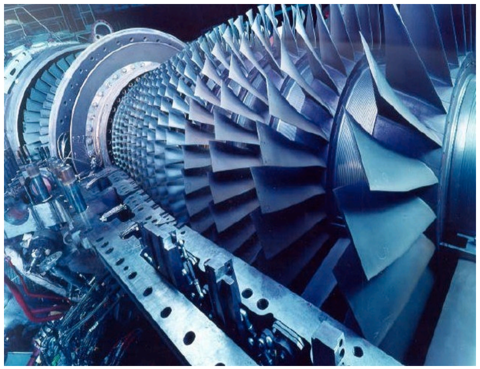
- **C_0 = «Normal»**
- **C_1 = «Anomaly of Type 1»**
- **C_2 = «Anomaly of Type 2»**

TRAINING



Real data «x_1,x_2,…x_n, ~~class~~»

Labels not available
Imbalanced classes



…

Empirical Classifier

(kNN, SVM, ANN,…)

- C_0 = «Normal»
- C_1 = «Anomaly of Type 1»
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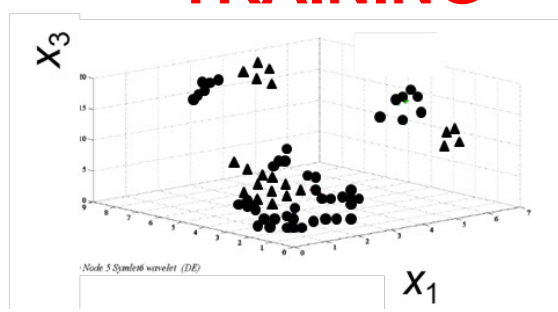
TRAINING



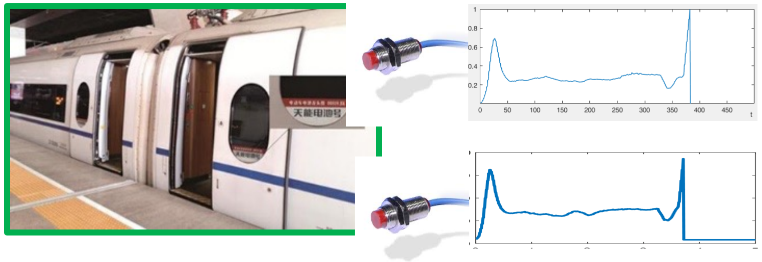
Real data «x_1,x_2,…x_n, ~~class~~»

Labels not available

Imbalanced classes

Data from other components of the same fleet

Example: Automatic Doors of a Fleet of High-Speed Trains



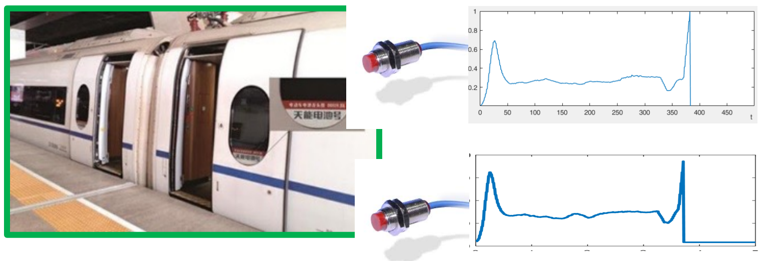
→ **AI Classifier** ↗

- Healthy
- Anomaly of type 1
- Anomaly of type 2
- Anomaly of type 3

➢ Relevance:

Faults of doors cause unavailability of the trains.

Example: Data (D)

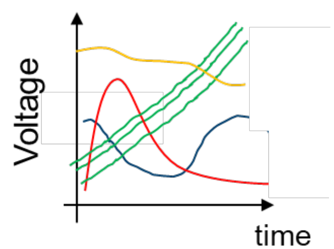


AI Classifier

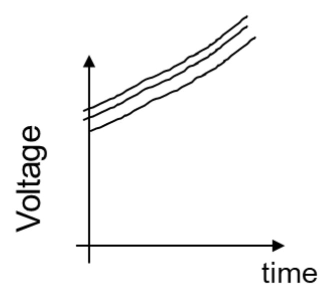
- Healthy
- Anomaly of type 1
- Anomaly of type 2
- Anomaly of type 3

TRAINING

Train A

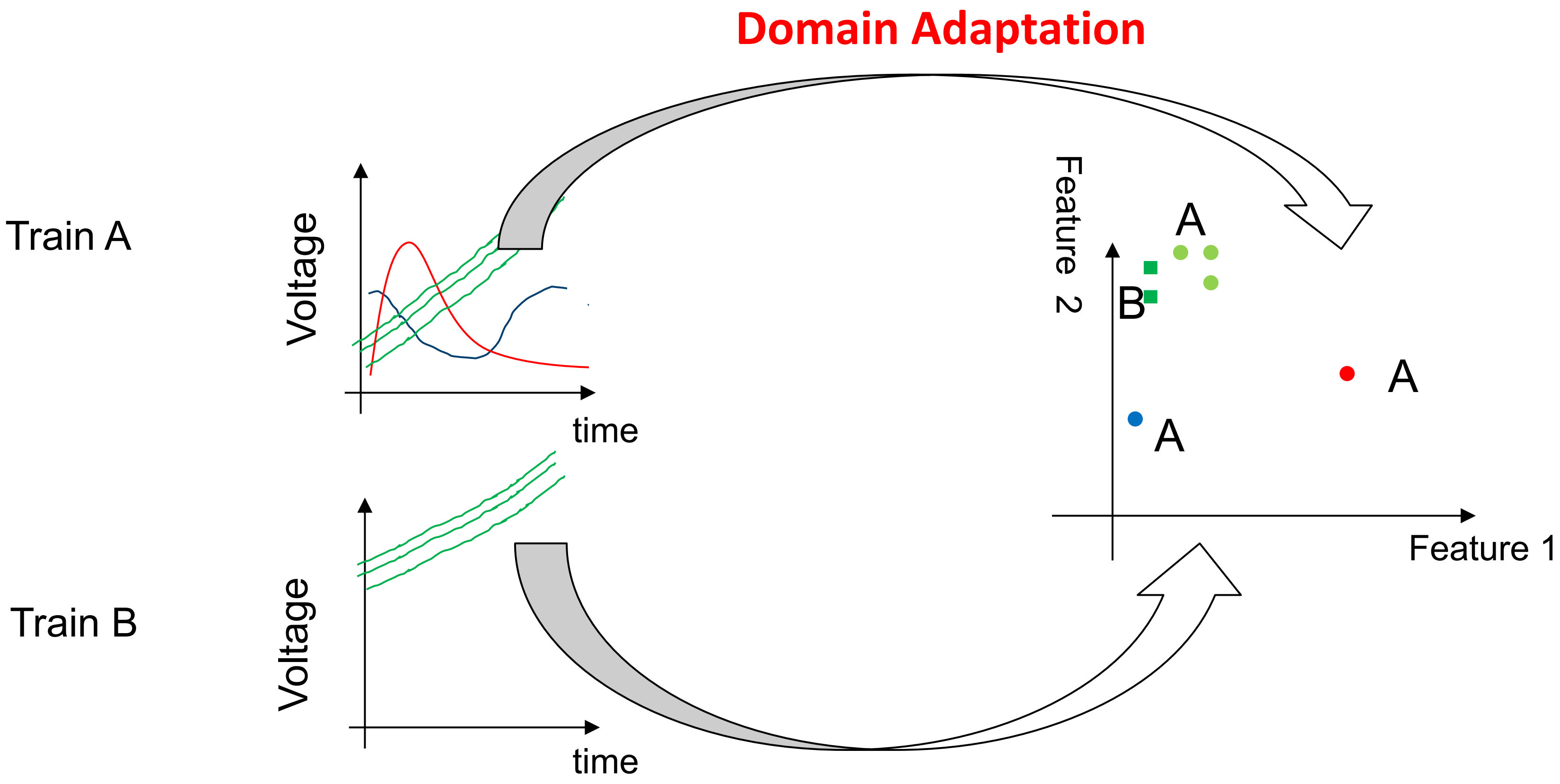


Train B

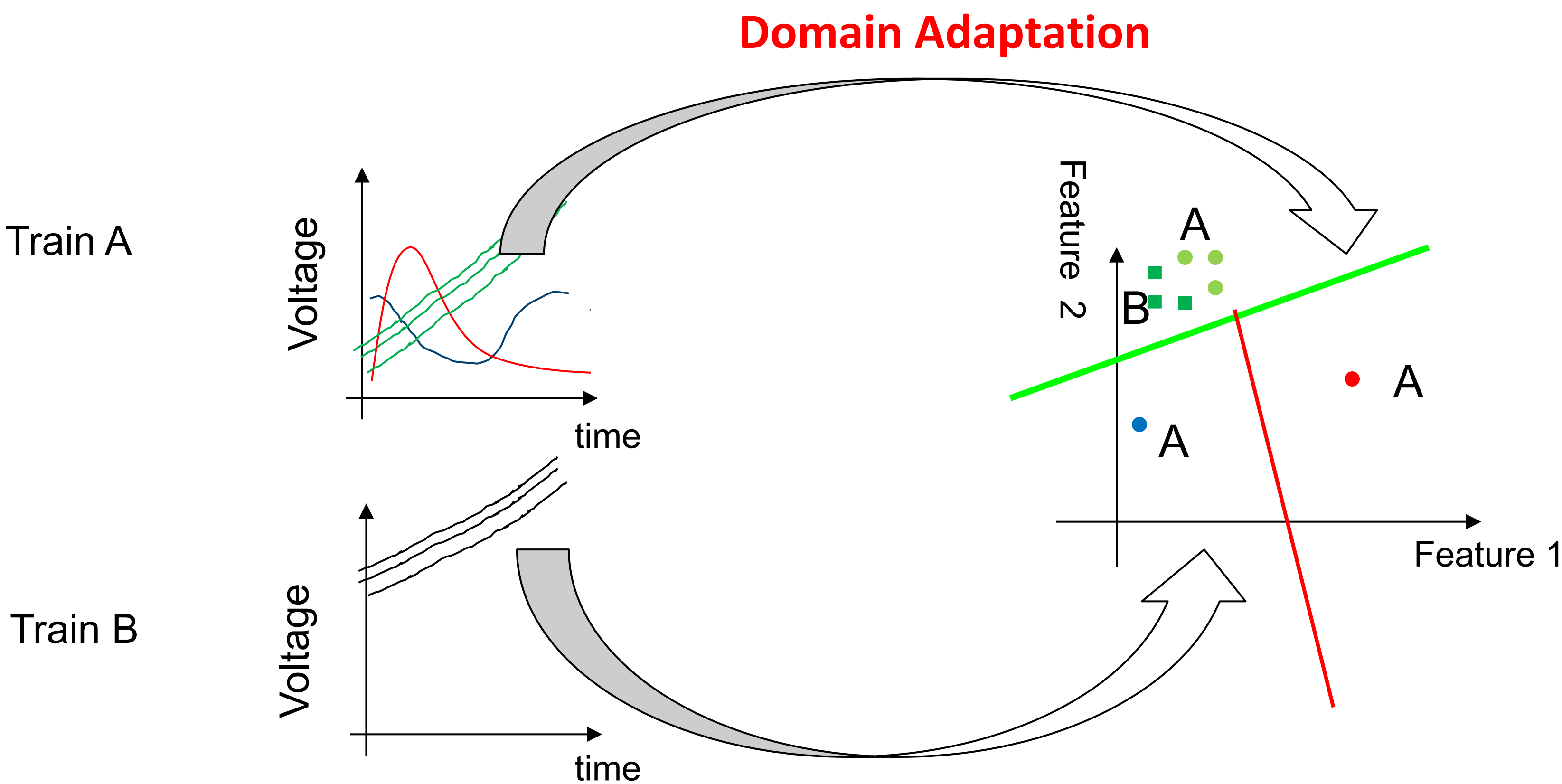


Unlabelled

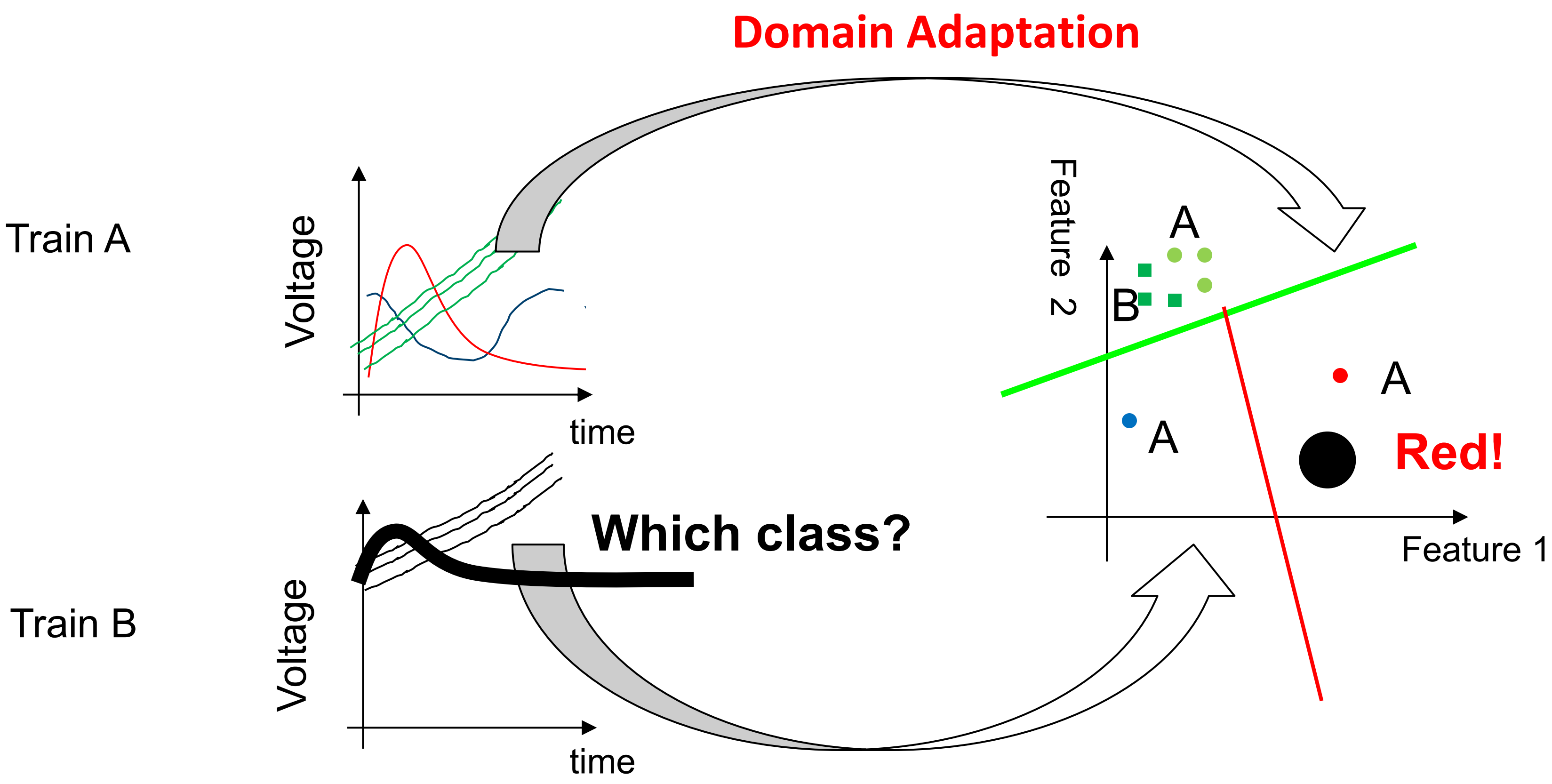
Example: Method



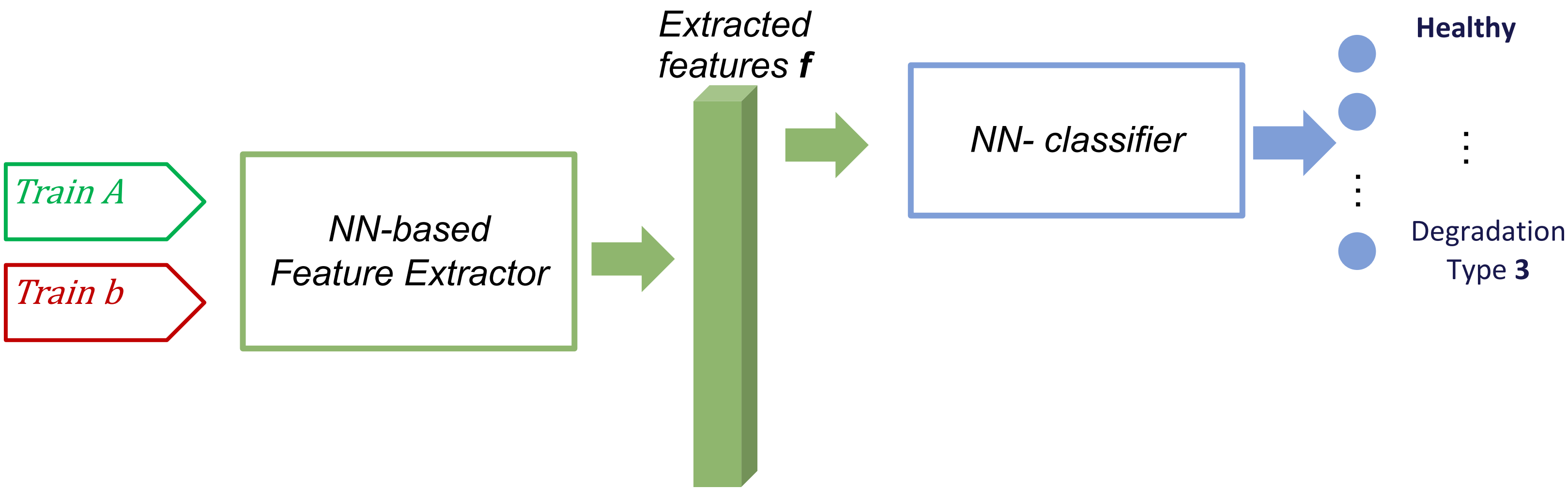
Example: Method

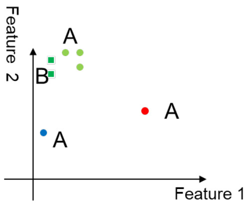


Example: Method

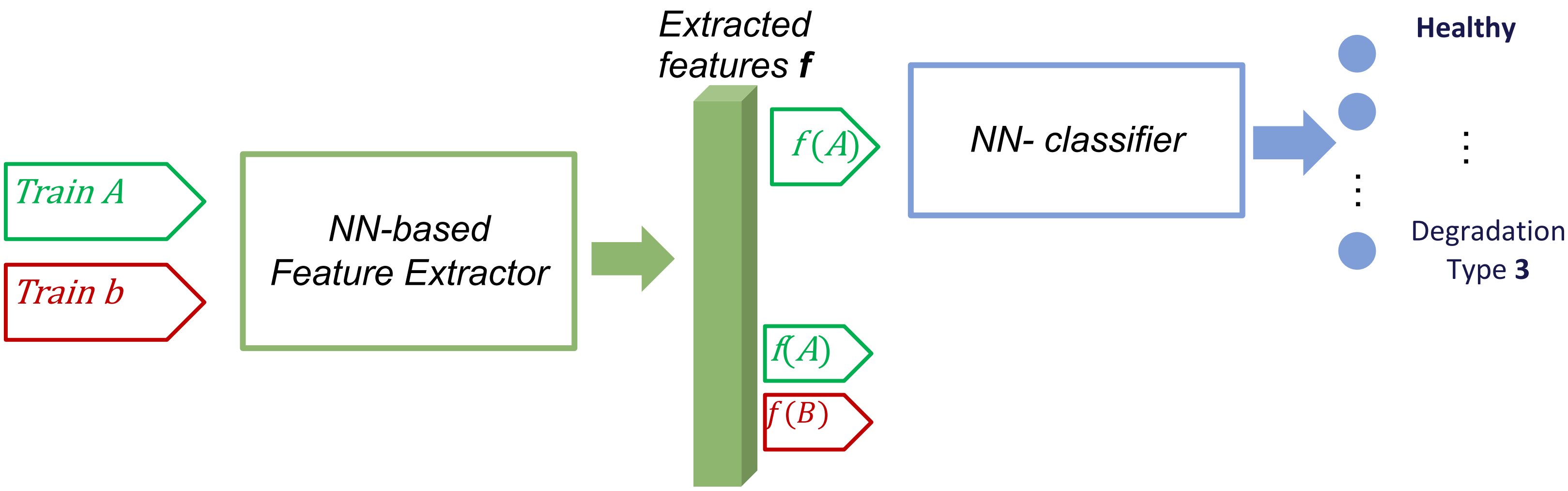


Example: Empirical Model – Adversarial Domain Adaptation



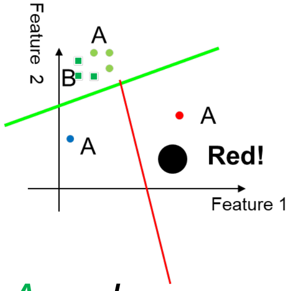


Example: Empirical Model – Adversarial Domain Adaptation

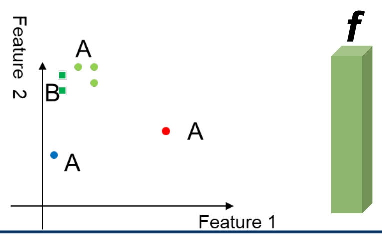


- **Training Objectives:**

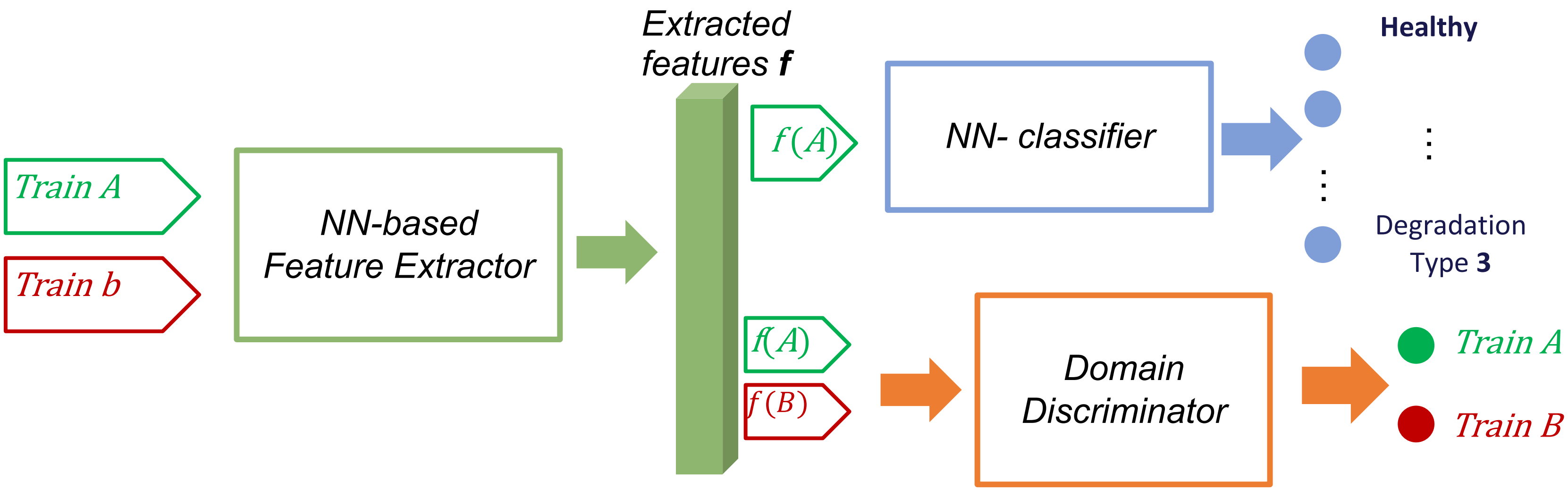
  1) Minimize classification error on Train A data



  2) Minimize divergence between Train A and Train B in the space of the extracted features

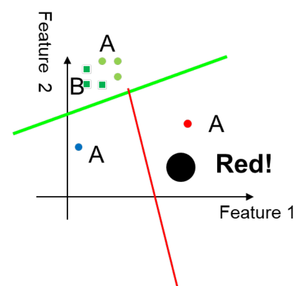


Example: Empirical Model – Adversarial Domain Adaptation

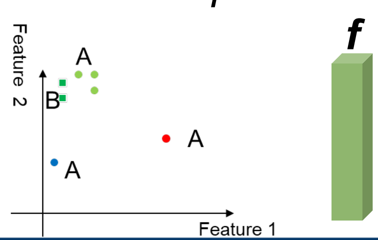


➢ **Training Objectives:**

1) Minimize *classification error* *on Train A data*



2) Minimize *divergence* *between Train A and Train B in the space of the extracted features*



Adversarial Learning:

NN-based Feature Extractor is trained to cheat *Domain Discriminator*

Example: Results

Classification Accuracy on Train B	*mean*	*std*
ANN trained using Train A labelled patterns	0.746	0.060
Adversarial domain adaptation method ***(Train A labelled patterns + 50% train B unlabelled patterns)***	**0.938**	**0.029**

* B. Wang, P. Baraldi, E. Zio, "*Deep Multi-Adversarial Conditional Domain Adaptation Networks for Fault Diagnostics of Industrial Equipment*", 2022, IEEE Transactions on Industrial Informatics, 19(8).

Example: Trustworthyness

Trustworthy Fault Diagnostics

Accurate

Consistent with Laws of Physics

Confident

Providing an Explanation of the Prediction

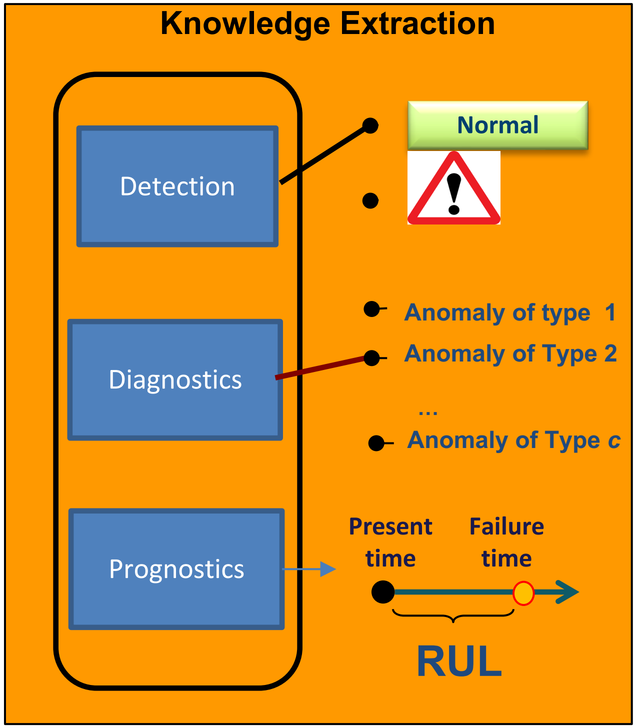
Domain Adaptation

Data from other components of the same fleet

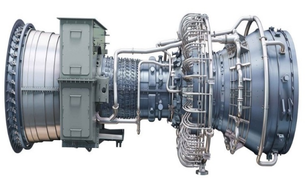
Industrial Systems:
- Some Characteristics

PHM:
- Fault Detection
- Fault Diagnostics
- Fault Prognostics

Conclusions

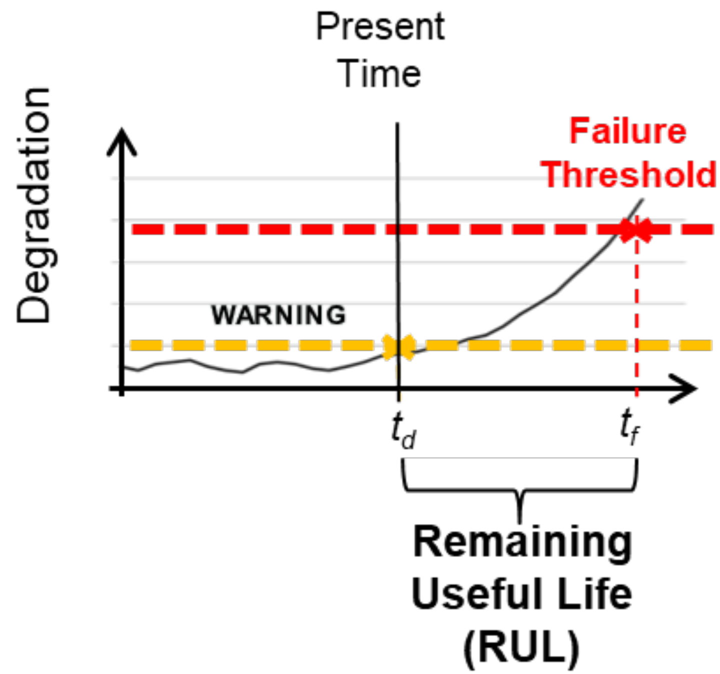


Fault Prognostics: Methods



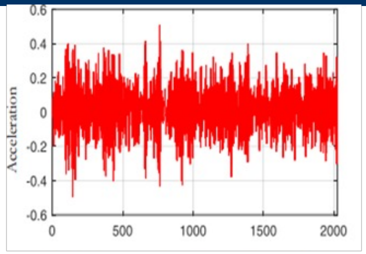
Prediction Model

Data Driven (ANN, RNN, RVM, Similarity-based,…)	Model-Based (Kalman Filter, Particle Filter,…)



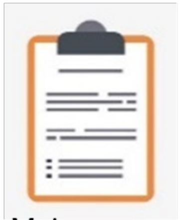
Fault Prognostics: Data (D) and Information (I)

(D)



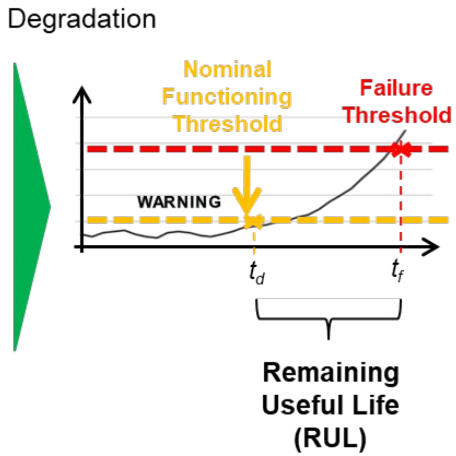
(D)

(I)

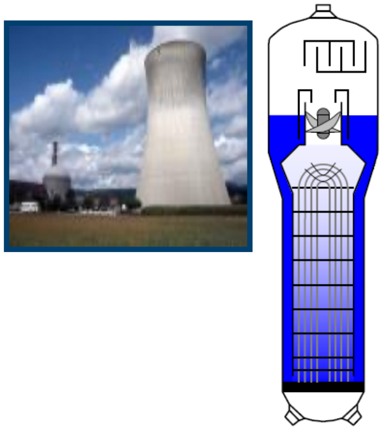


Maintenance records

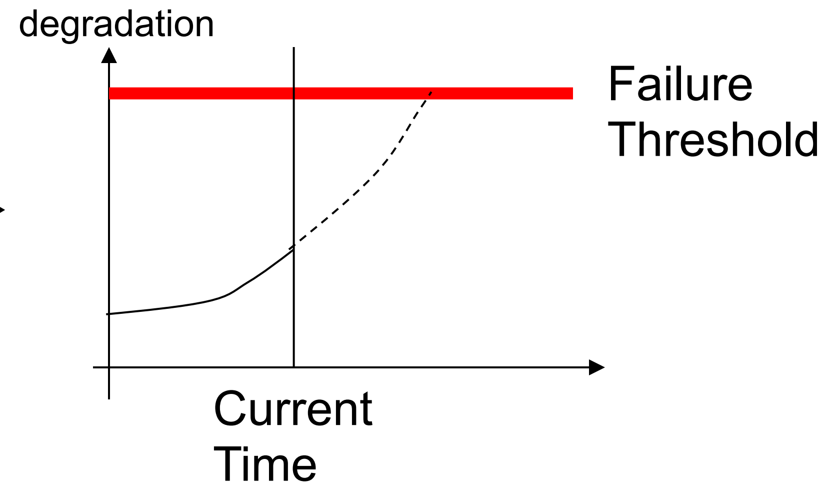
Prediction Model (Data-driven)



Example: Steam Generator of a Nuclear Power Plant



Prognostic Model



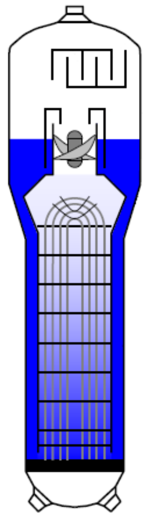
Degradation mechanisms:
- Clogging of tube support plates
- Tube fouling

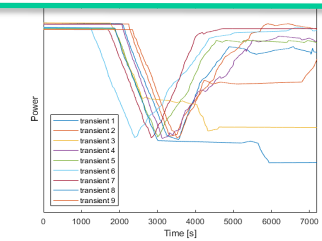
malfunctioning

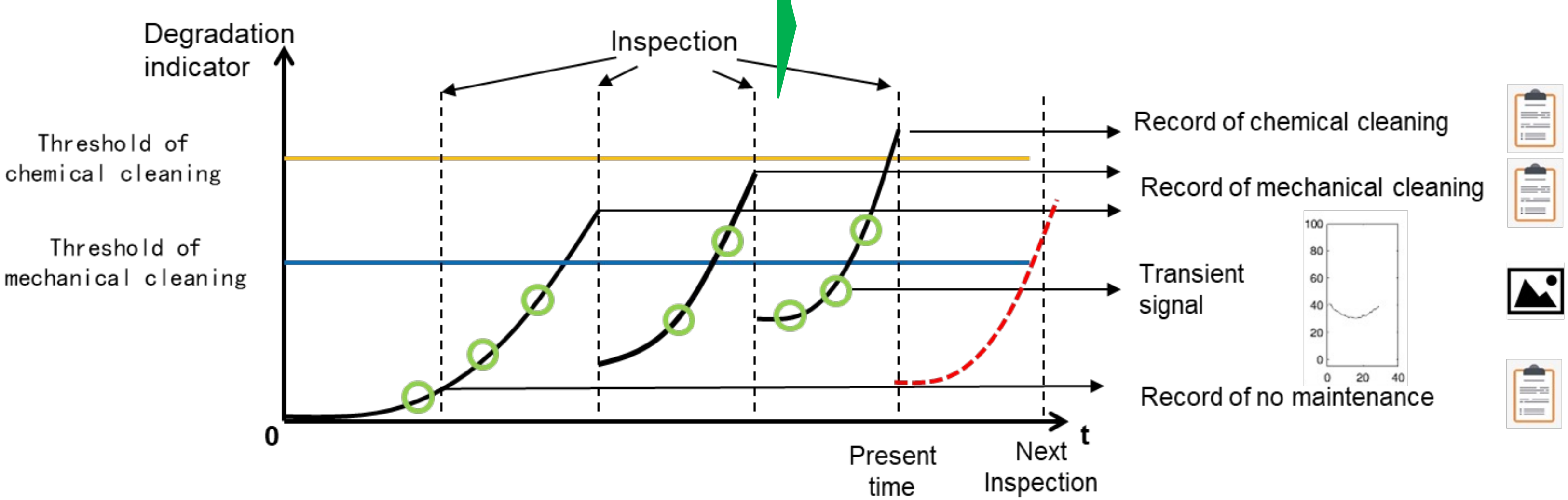
plant outage

Maintenance interventions:
- Mechanical cleaning (partial removal of deposit)
- Chemical cleaning ($$$,long unavailability)

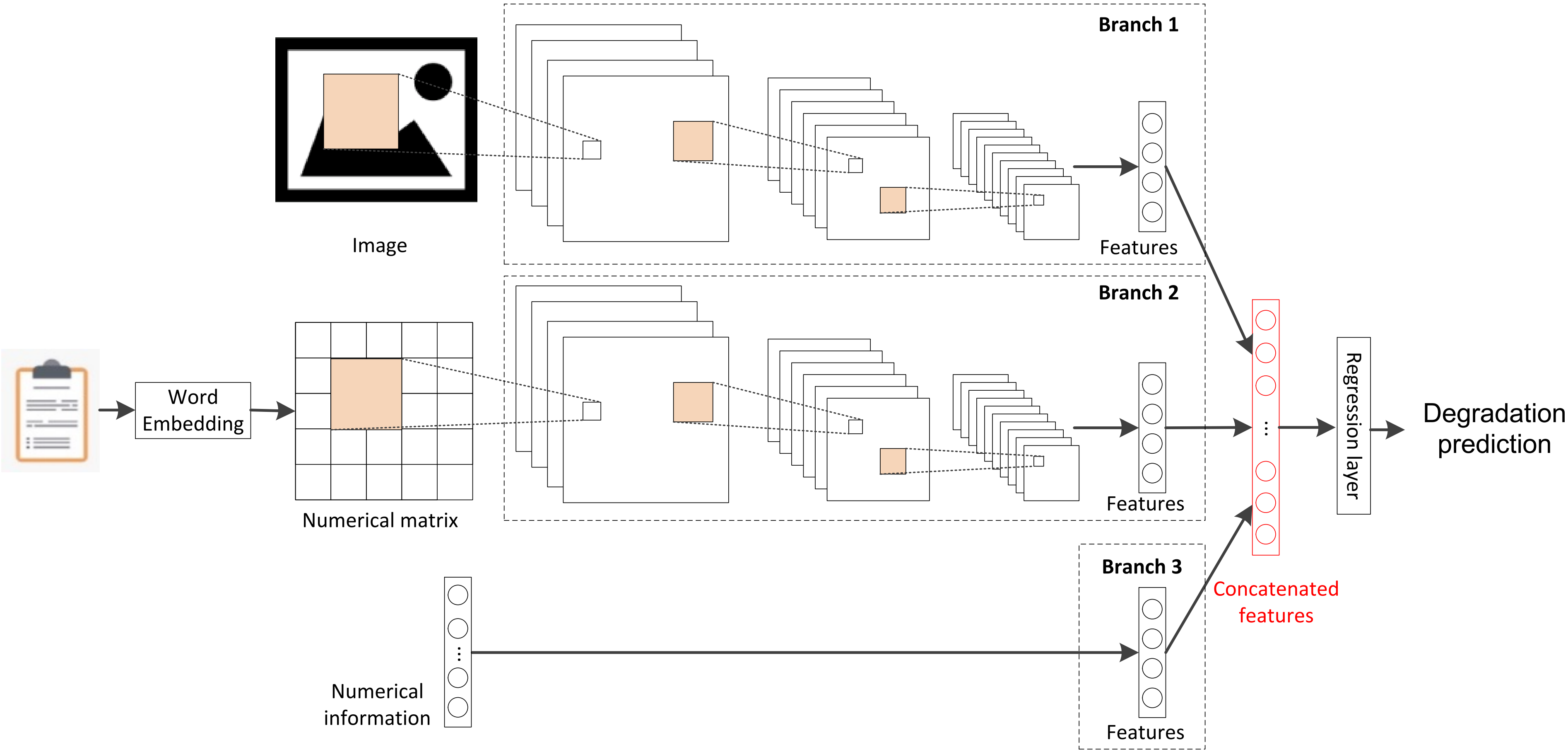
Example: Data and Information (K)ID



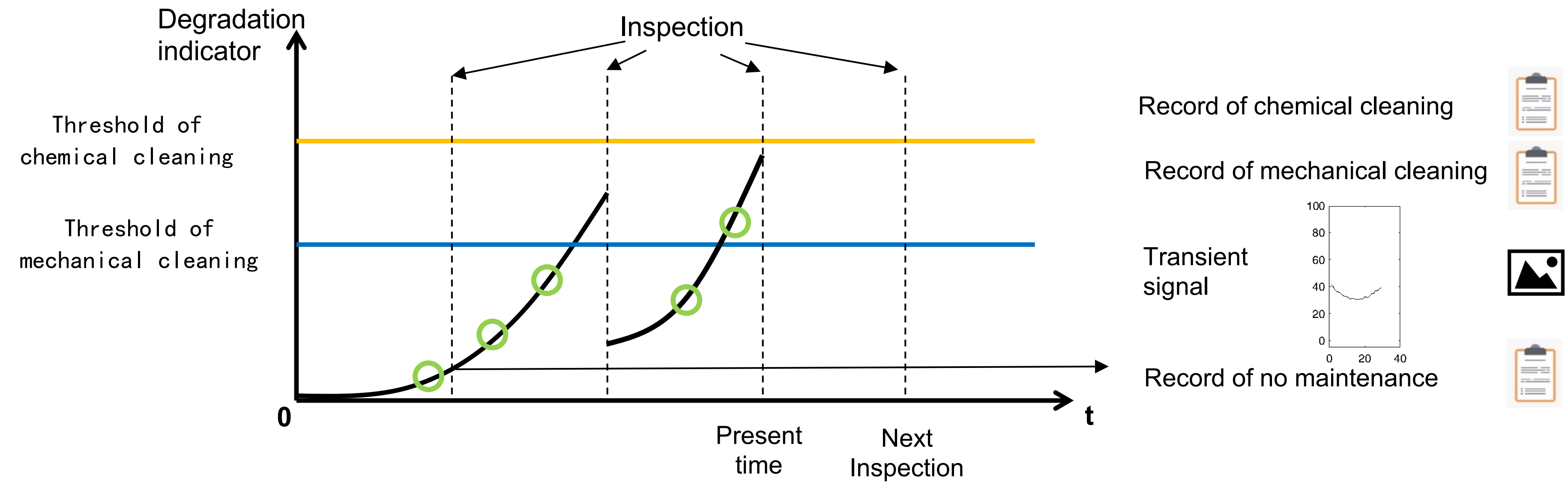
Numerical Values	• Time from last inspection • Number of performed chemical cleanings • Number of performed mechanical cleanings		**(D)**
Images	Signal evolution during plant transients		**(D)**
Texts	Inspection reports	Description of the condition of SG based on nondestructive testing and maintenance intervention	**(I)**



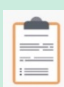
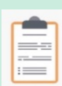
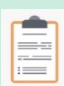
Example: Empirical Model - Multi-branch Deep Neural Network



Example - Results



Prediction of the SG degradation at the next planned Inspection (50 Steam Generators)

	The best model using one source of information	**The best model using two sources of information**	**Proposed method**
Sources of information		 	  
Mean Relative Error	10.7%	7.8%	6.8%

Z. Yang, P. Baraldi, E. Zio, "*A multi-branch deep neural network model for failure prognostics based on multimodal data*", Journal of Manufacturing Systems, 59, pp. 42-50, 2021.

Example: Trustworthyness

Trustworthy Fault Prognostics

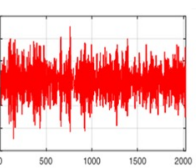
Accurate

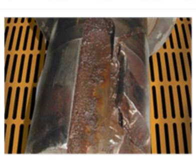
Consistent with Laws of Physics

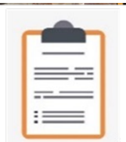
Confident

Providing an Explanation of the Prediction

Multi-branch Deep Neural Network

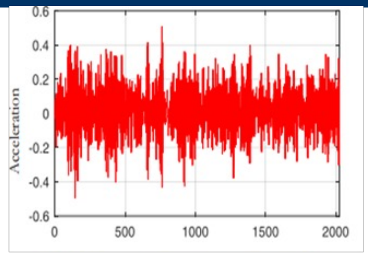


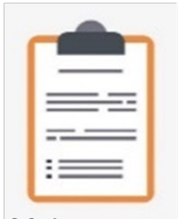




Maintenance records

Fault Prognostics: Data (D)

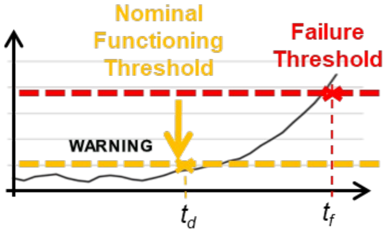




Maintenance records

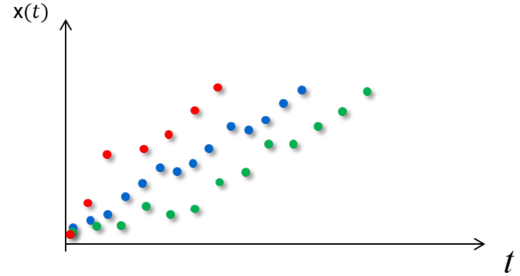
Prediction Model (Data-driven)

Degradation



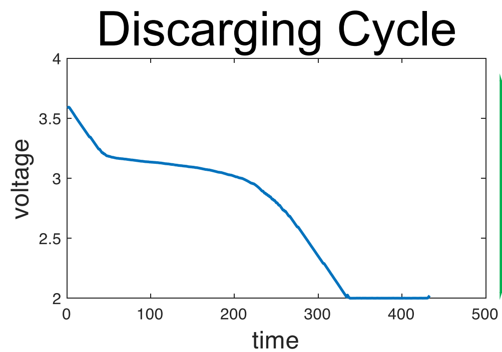
Remaining Useful Life (RUL)

TRAINING



Few run-to-failure trajectories from in-field applications

Example: Li-Ion Battery

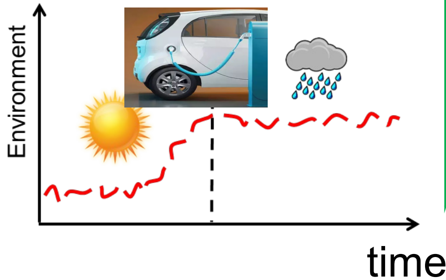


Prognostic Model → RUL

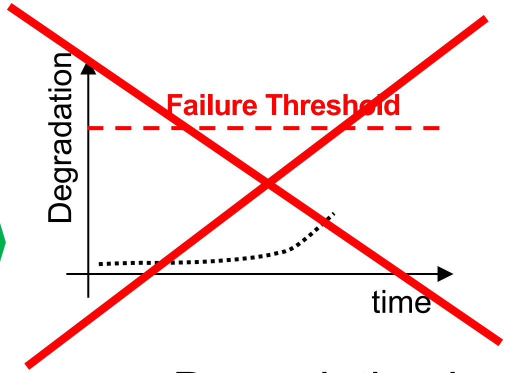
- Li-Ion Battery:
  - high-power density
  - low self-discharge
  - relatively long life
  - high cost
  - risk of flame ignition

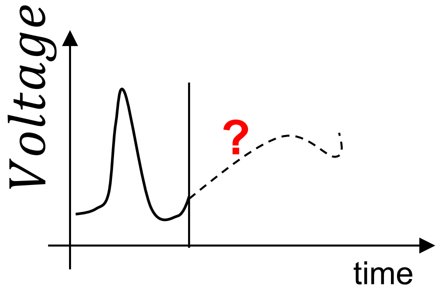
Predictive Maintenance to avoid failure:
- System safety ↑
- System availability ↑

Example: Data



In-field Applications

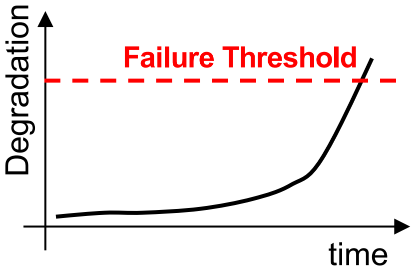


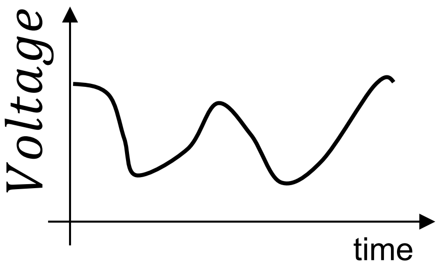


- Degradation is not measurable
- Few incomplete trajectories

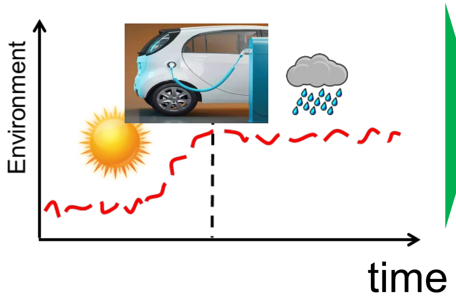
Example: Data

Laboratory
(controlled environment)

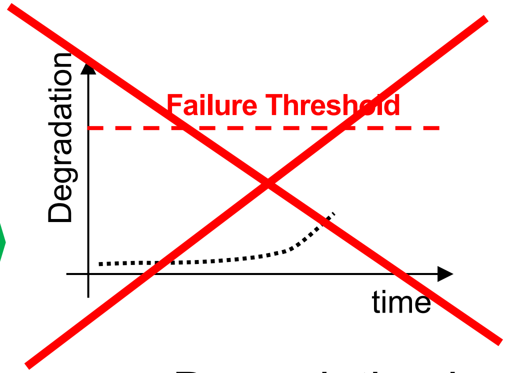


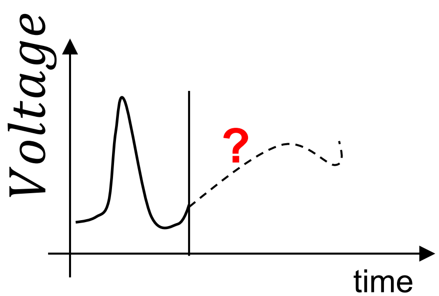


- Run to Failure trajectories
- Measure degradation



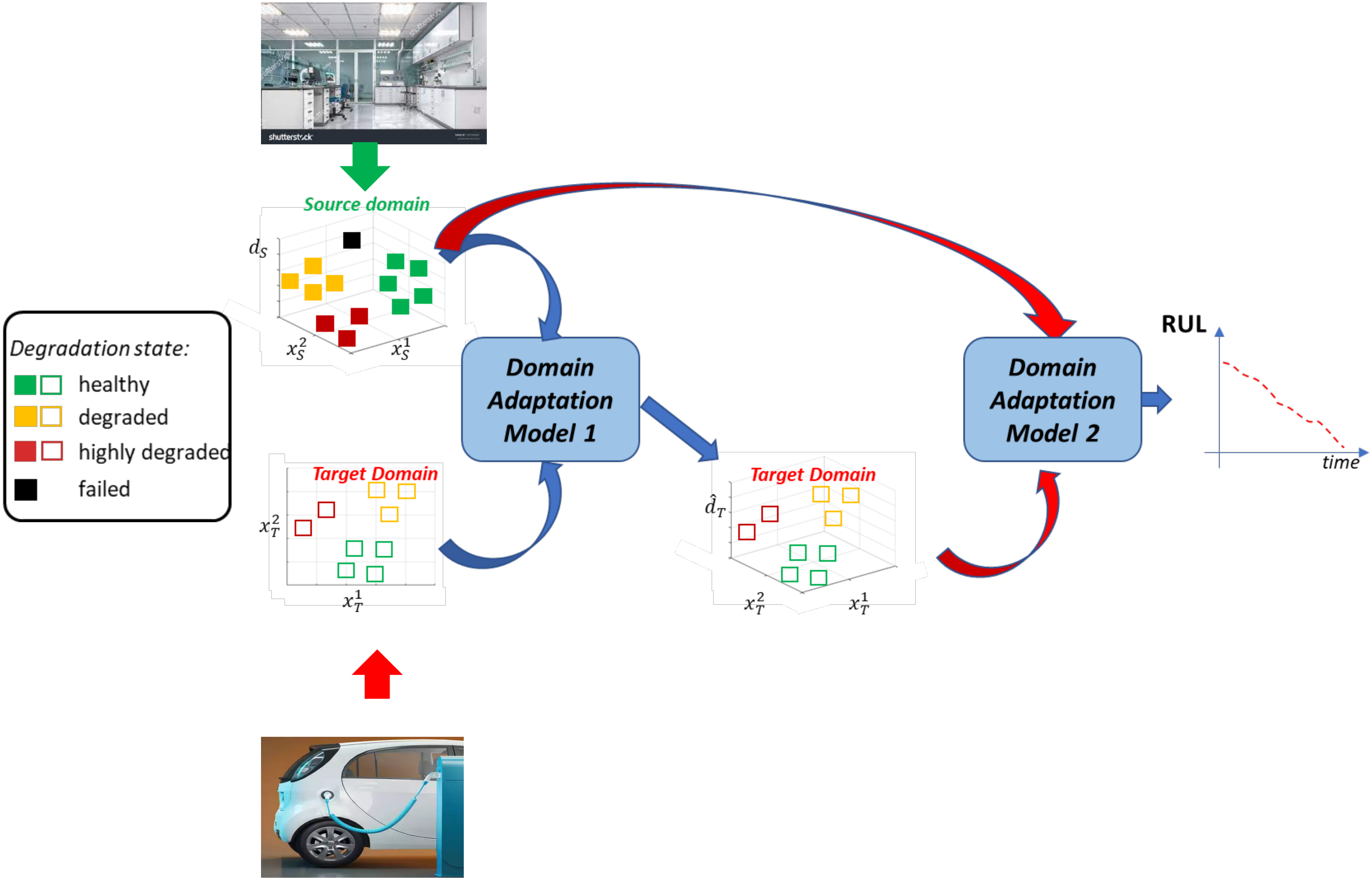
In-field Applications



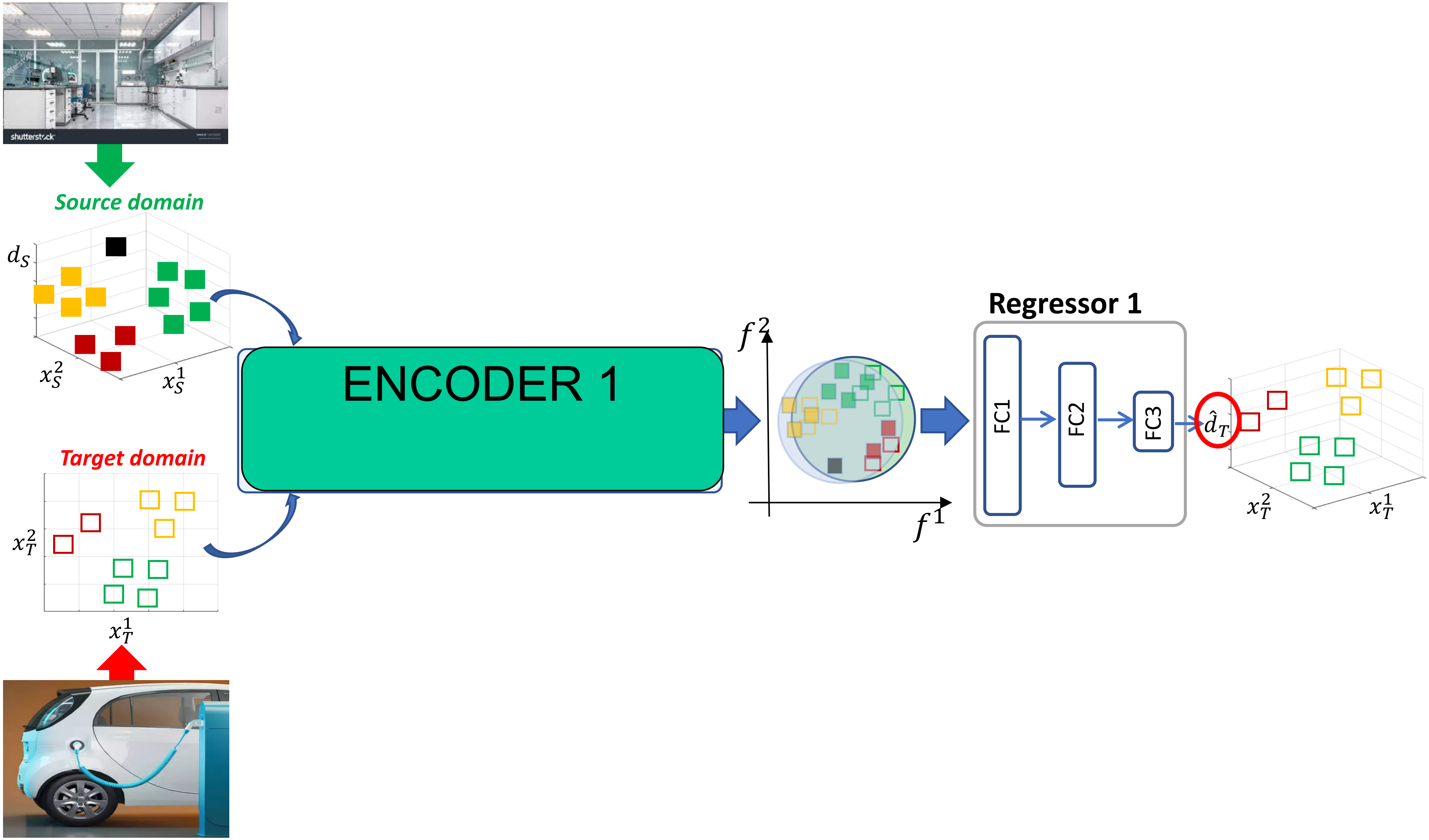


- Degradation is not measurable
- Few incomplete trajectories

Example: Empirical Model – Heterogeneous Transfer Learning

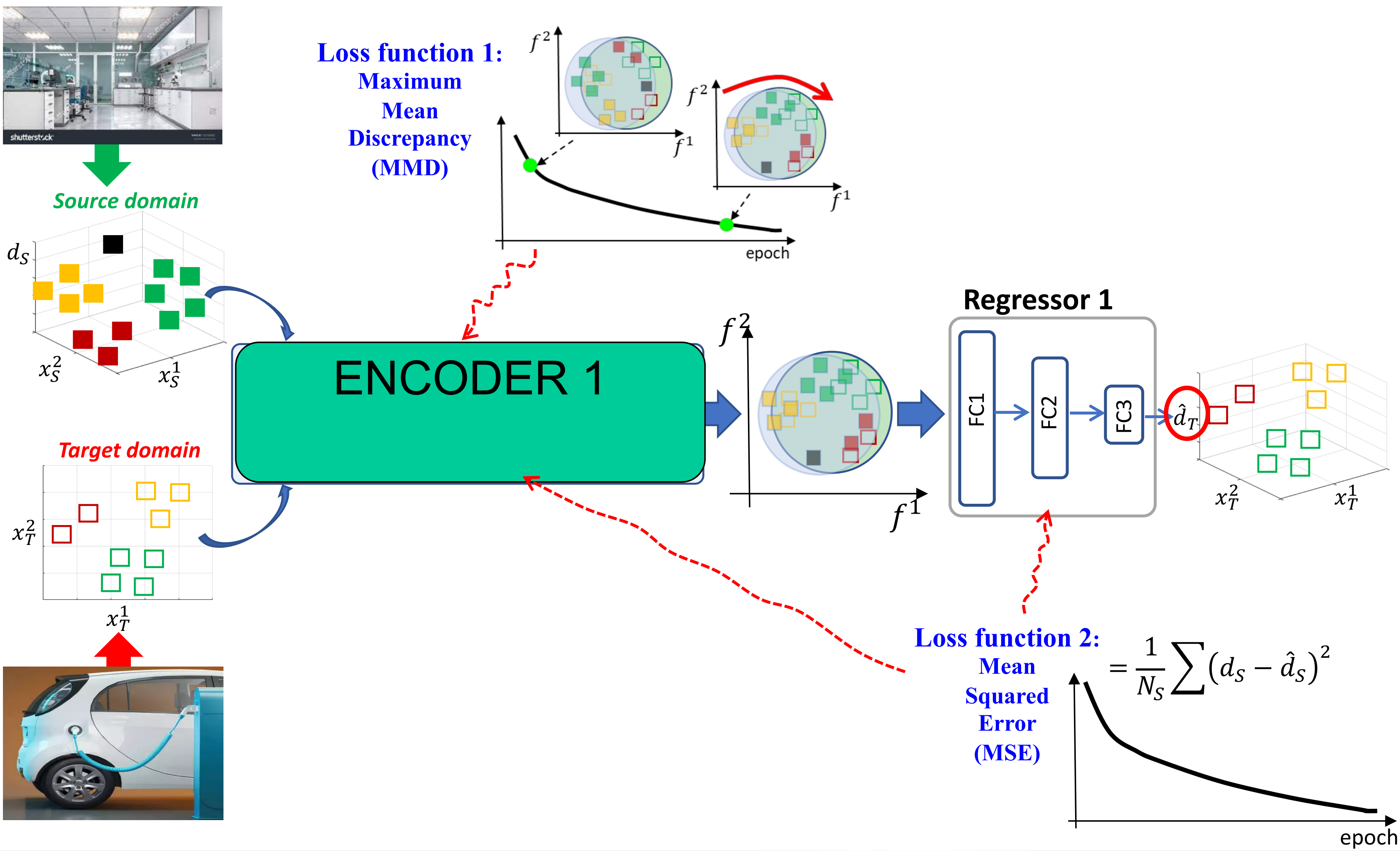


Example: Empirical Model - Heterogeneous Transfer Learning

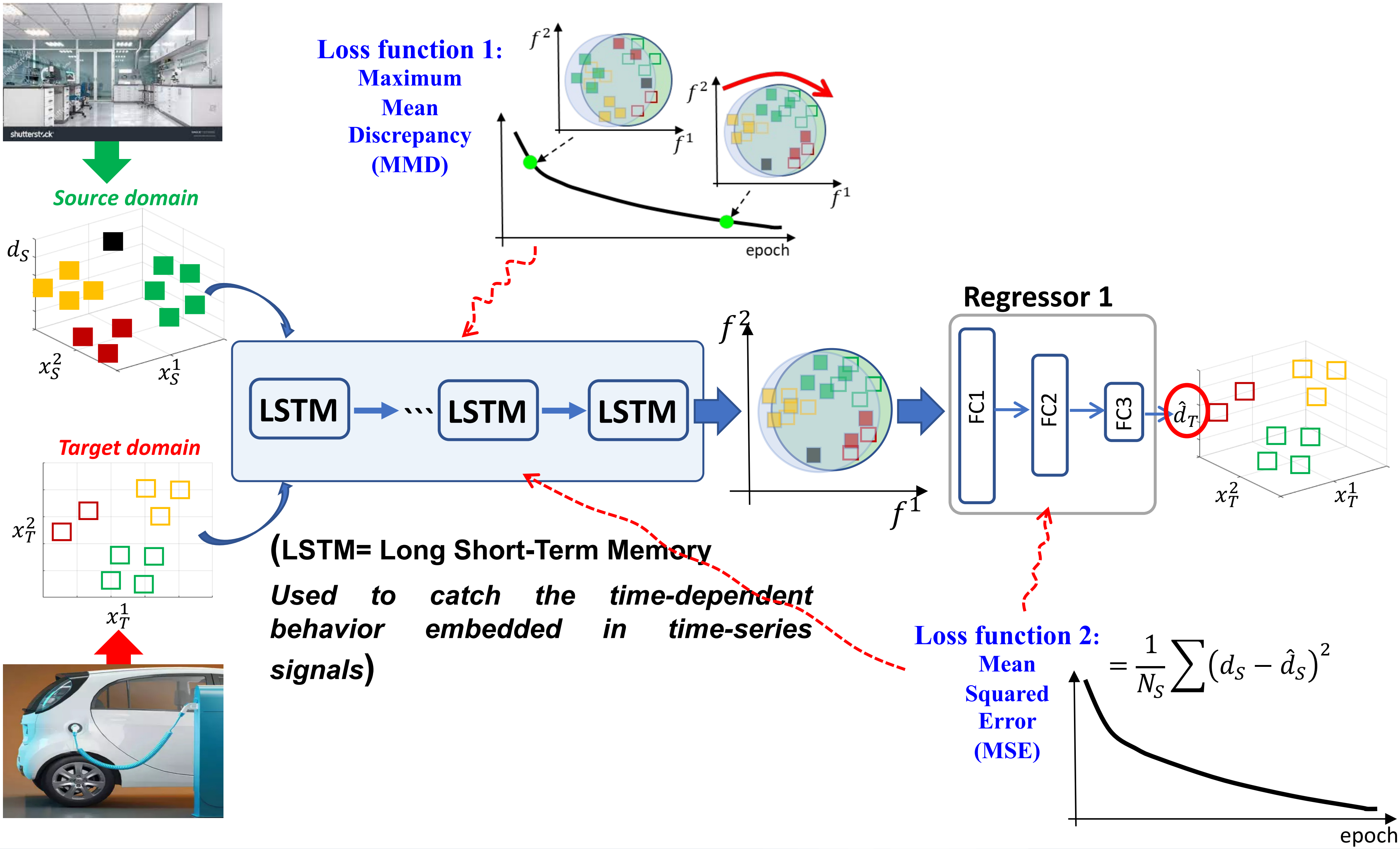


epoch

Example: Empirical Model - Heterogeneous Transfer Learning



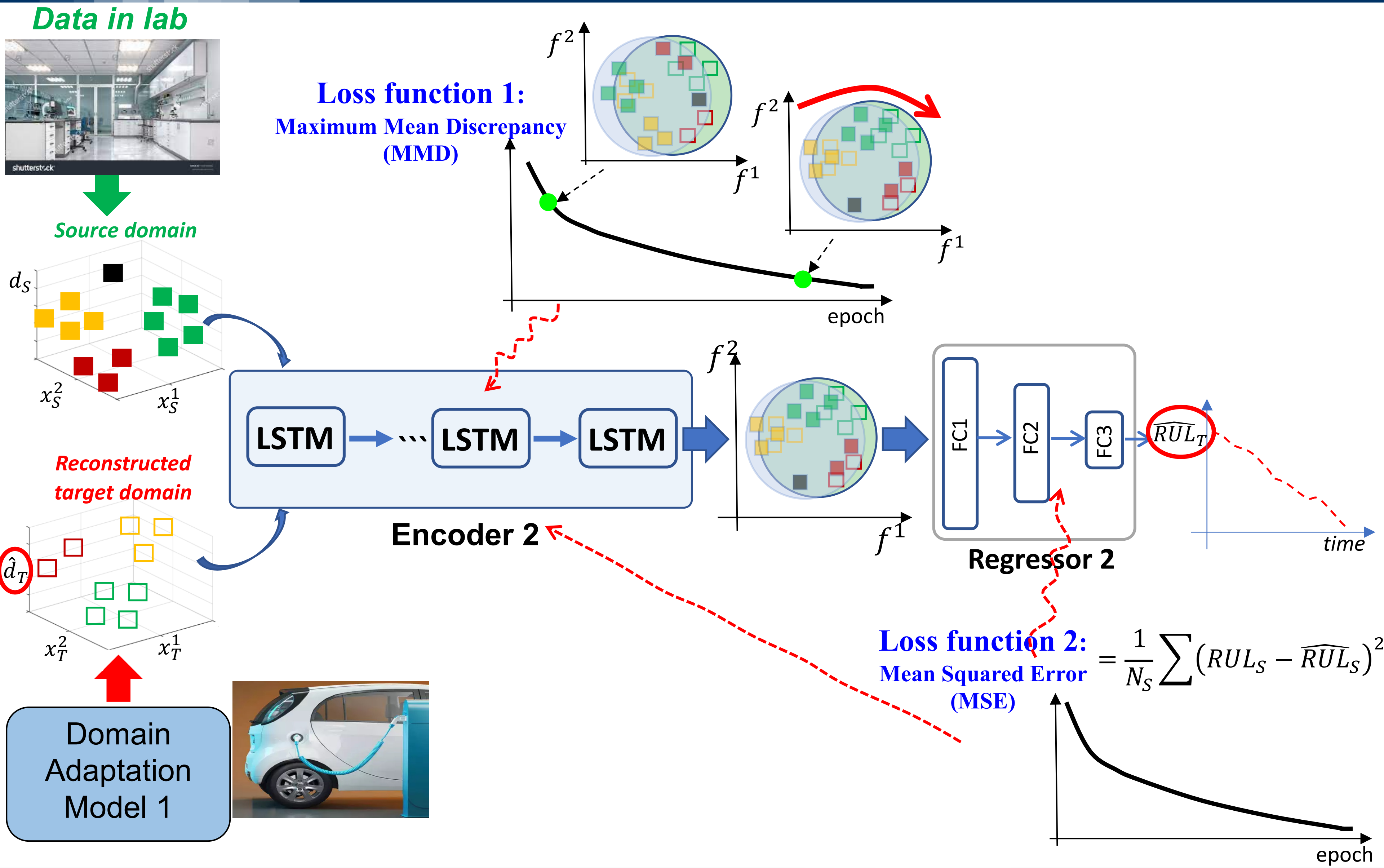
Example: Empirical Model - Heterogeneous Transfer Learning



(LSTM= Long Short-Term Memory

***Used to catch the time-dependent behavior embedded in time-series signals*)**

Example: Empirical Model - Heterogeneous Transfer Learning

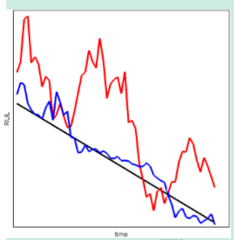


Example: Results

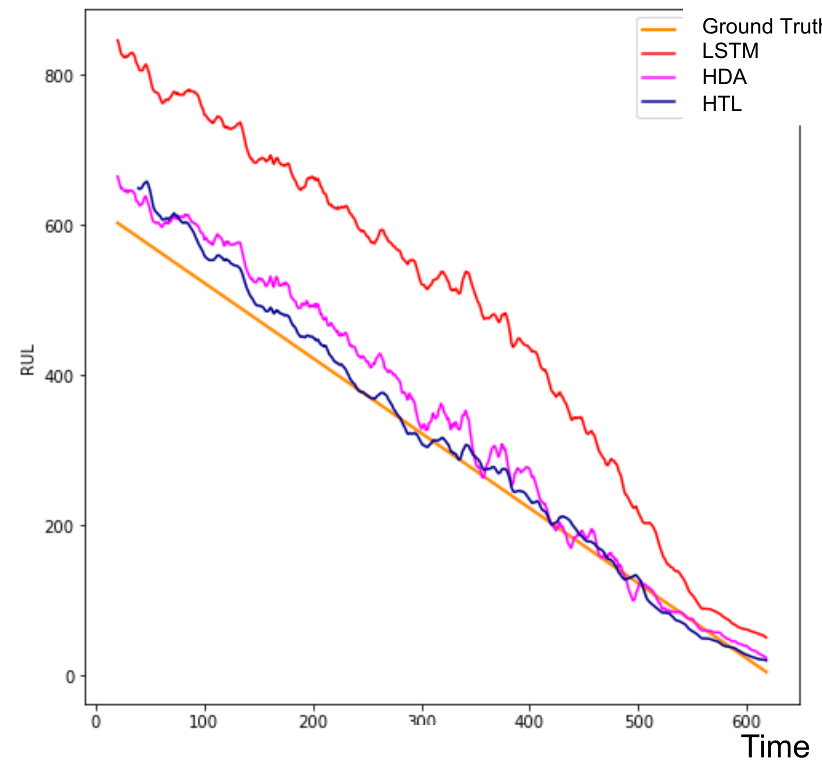
Method	Performance Metric: Cumulative Relative Accuracy
Traditional LSTM Model *(no use of in-field data)*	0.24
Homogeneous Domain Adaptation (HDA) *(no use of degradation data in source domain)*	0.81
Heterogeneous Transfer Learning (HTL) ***(developed method)***	**0.87**

$$RA = 1 - \frac{\left| R\widehat{U}L - RUL^{GT} \right|}{RUL^{GT}}$$

RUL



Time



RUL predictions of one test battery (In-field Application)

Example: Trustworthyness

Trustworthy Fault Prognostics

Accurate

Consistent with Laws of Physics

Estimation of Uncertainty of the Prediction

Providing an Explanation of the Prediction

Domain Adaptation

Few run-to-failure trajectories from in-field applications

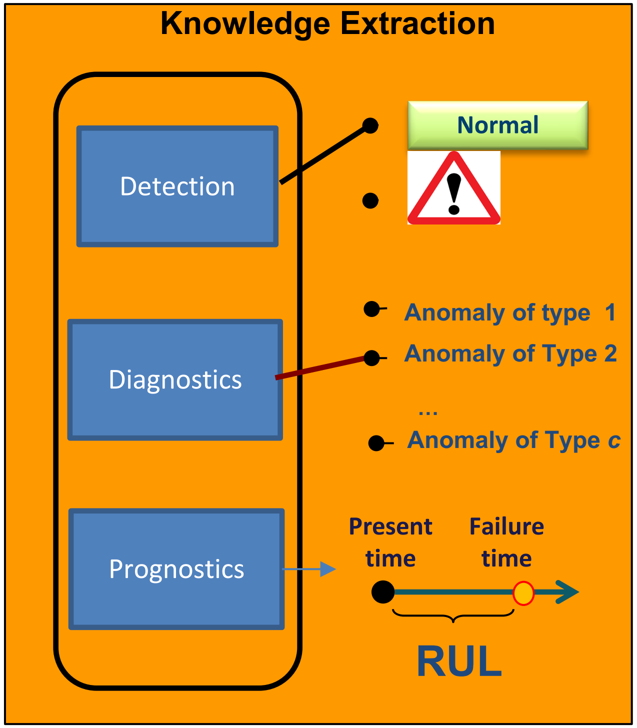
Industrial Systems:

- Some Characteristics

PHM:

- Fault Detection
- Fault Diagnostics
- Fault Prognostics

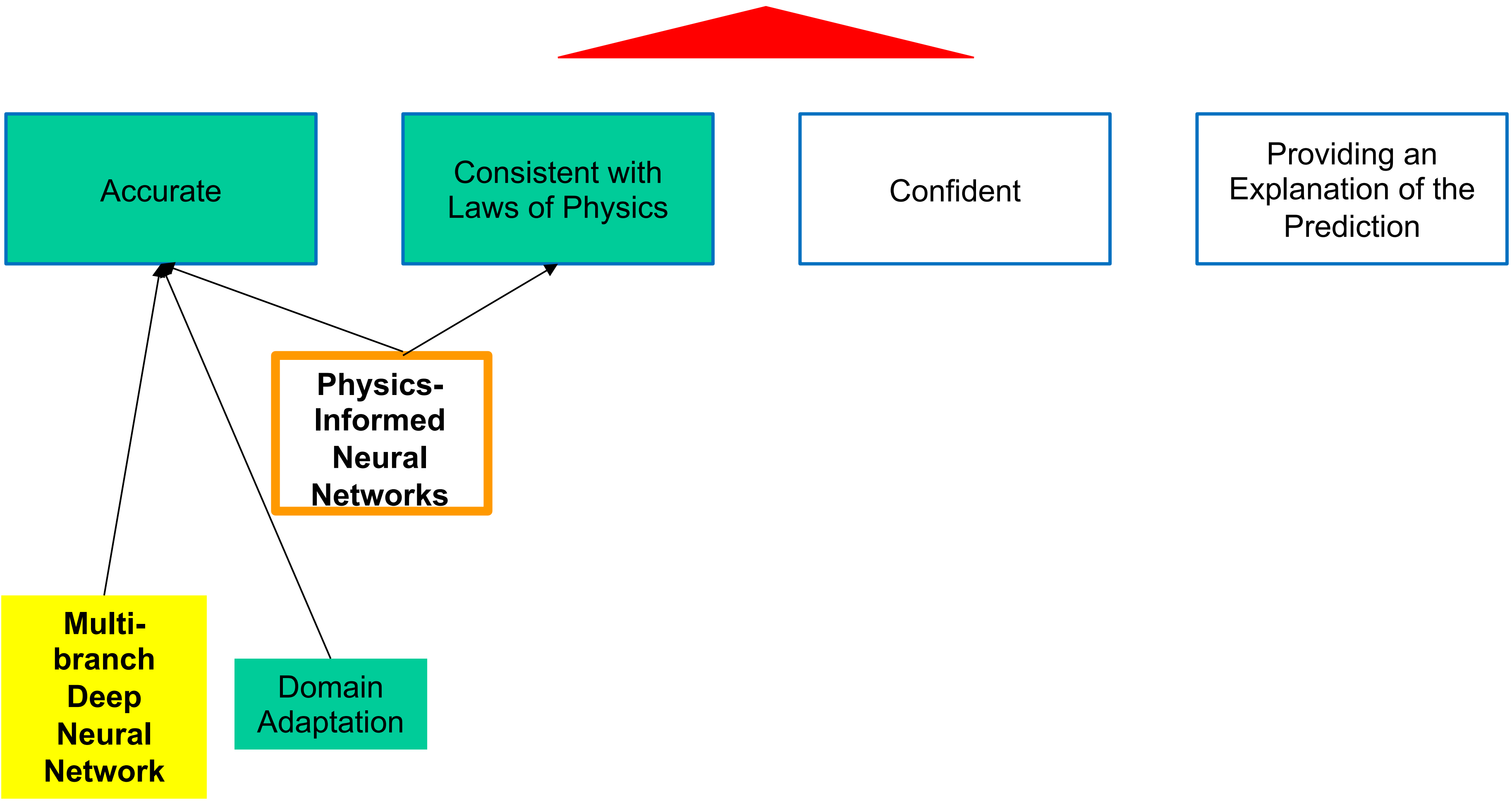
Conclusions



Trustworthy PHM

Accurate	Consistent with Laws of Physics	Confident	Providing an Explanation of the Prediction

Trustworthy PHM



AI for PHM: How Can We Trust It?

Trustworthy PHM

Accurate

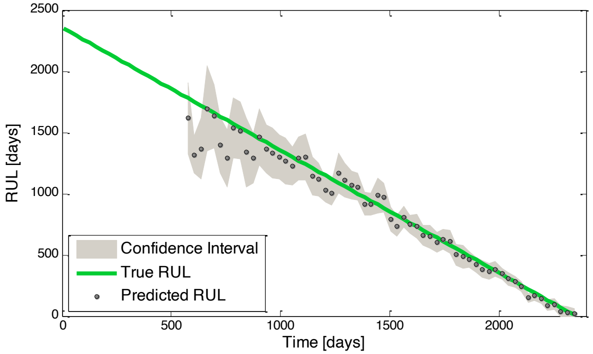
Consistent with Laws of Physics

Confidence

Providing an Explanation of the Prediction

Sources of uncertainty:
1) noise on the measurements
2) stochasticity of the degradation process
3) unknown future external/operational conditions
4) Modeling errors, i.e. inaccuracy of the prognostic model used to perform the prediction

- **Bootstrapped Ensemble**
- **Monte Carlo Dropout**
- **…**



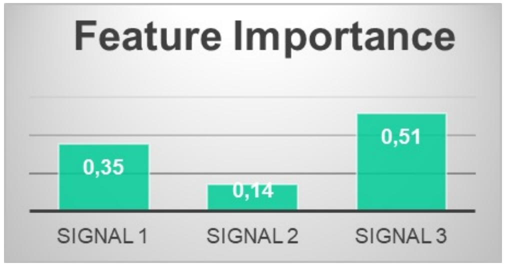
Baraldi P., Mangili F., Zio E.; «Investigation of uncertainty treatment capability of model-based and data-driven prognostic methods using simulated data»; (2013) Reliability Engineering and System Safety, 112, pp. 94 - 108

AI for PHM: How Can We Trust It?

Trustworthy Artificial Intelligence

Accurate	Consistent with Laws of Physics	Confident	Providing an Explanation of the Prediction

eXplainable AI:
- LIME
- SHAP
- CARTOONX
- …

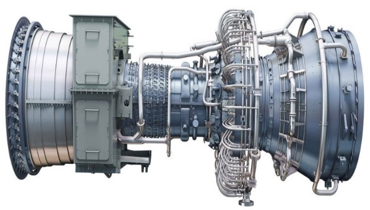


RUL is 57 H because of Signal 3 strange behaviour

Insulator is classified as broken because of this area

Floreale, G., Baraldi, P., Zio, E., & Fink, O. (2023). *Exploiting Explanations to Detect Misclassifications of Deep Learning Models in Power Grid Visual Inspection*. 33rd European Safety and Reliability Conference (ESREL 2023) 3 – 8 September 2023, Southampton, UK.

Conclusion: PHM – When Will We Trust It?



AI-based PHM Model

→ It is degraded due to creeping

It is going to fail in: 57:25:18

I believe it! I will do maintenance within 3 days

- Accurate
- Consistent with Laws of Physics
- Estimation of Uncertainty of the Prediction
- Providing an Explanation of the Prediction

THANK YOU FOR YOUR ATTENTION