Anomaly detection for complex equipment monitoring

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Anomaly detection for complex equipment monitoring

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Business problematic

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1 Business problematic

SMART EXCEPTION : Application cases

Cranes

Wind Turbines

Stamping presses

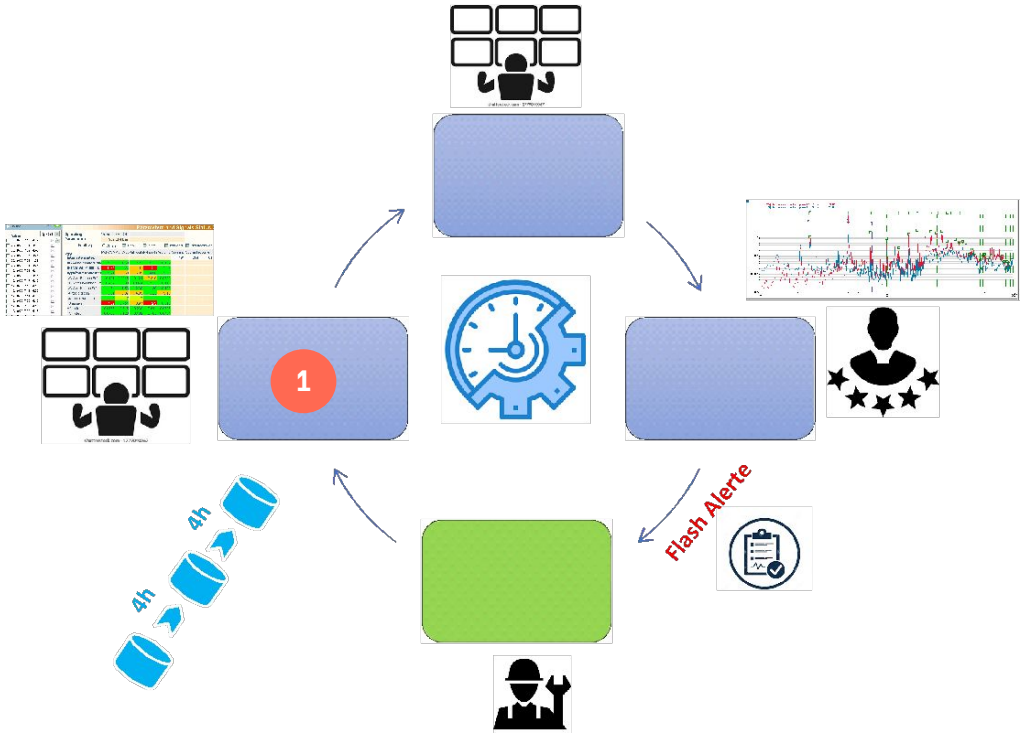
Papermills

Dedicated to “complex” equipments :

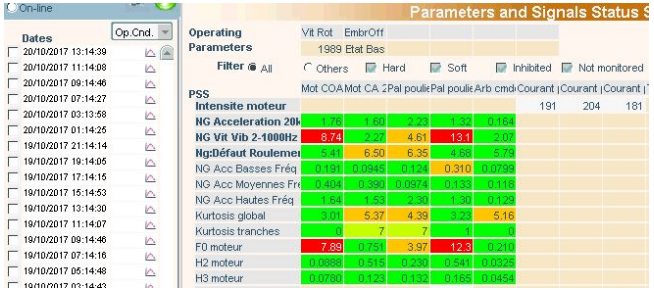
- Many mechanical components
- Fast varying conditions, intermittent regimes with strong impact on vibrations
- With many different potential defaults, outside “standard rotating machine” default catalog

Usage of self adaptive (non supervised) AI techniques

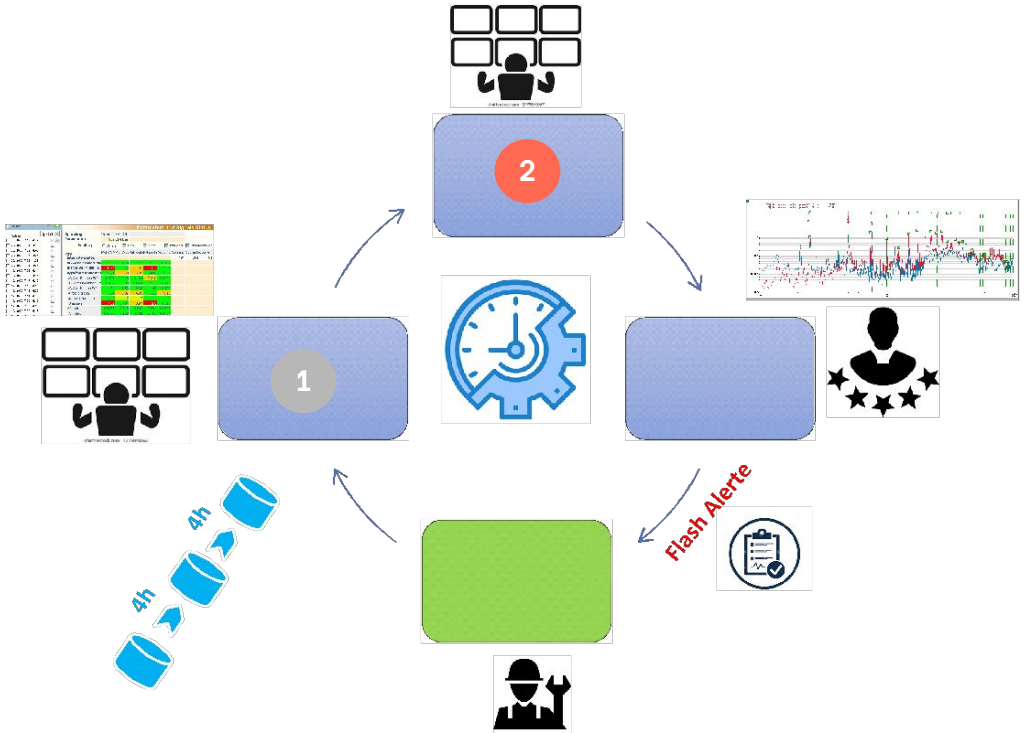
How works a Control Room ?



1 Control room technician : Follow with **Nesti4™**
Detection of machines of interest when **thresholds are exceeded**



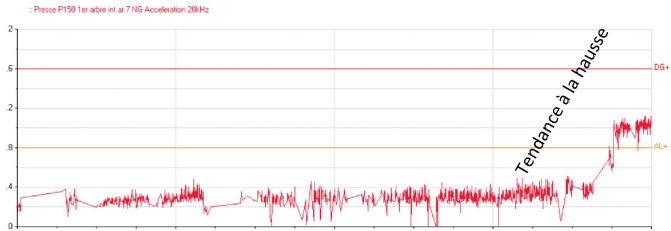
How works a Control Room ?



1 Control room technician : Follow with **Nesti4™**
Detection of machines of interest when **thresholds are exceeded**

If exceeded

2 Control room technician: Indicator **trend analysis**



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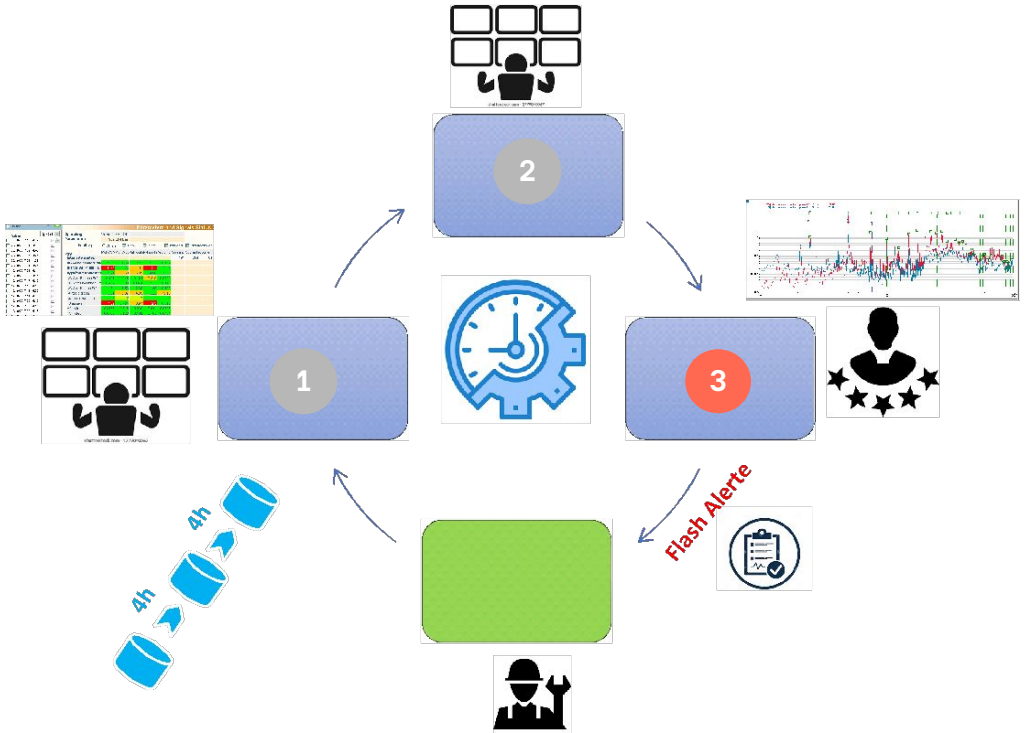

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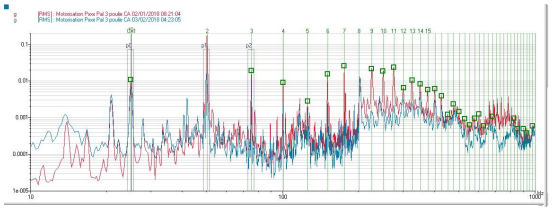
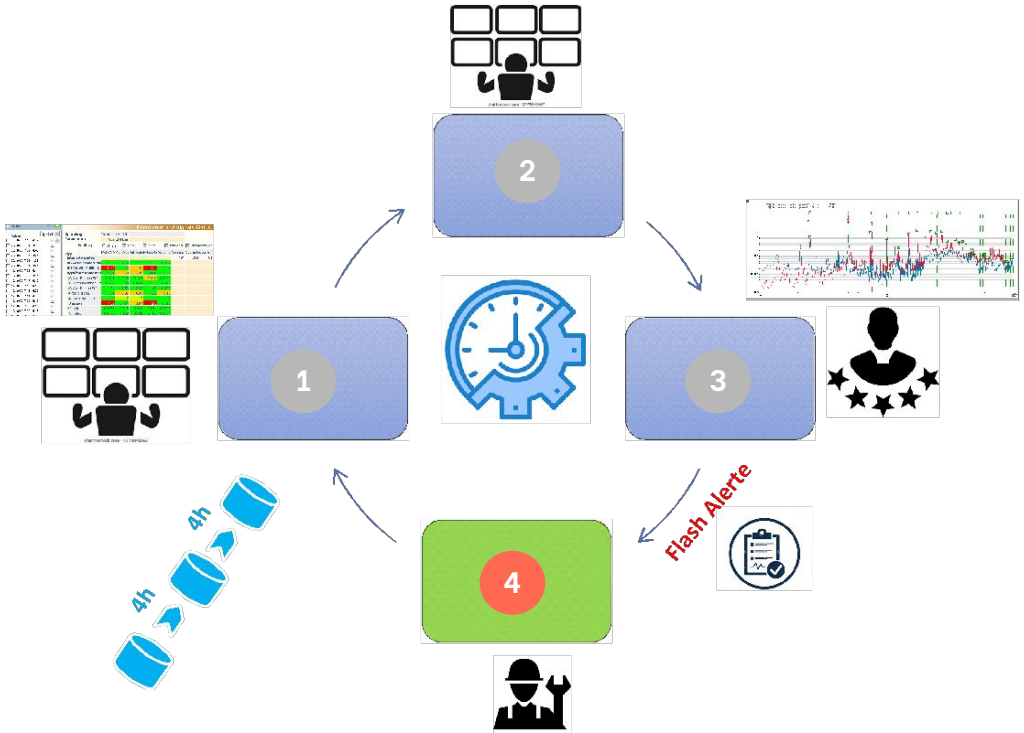
2 Control room technician: Indicator **trend analysis**

If uptrend

3 Expert: Signal analysis and **diagnostics**



How works a Control Room ?



1. Control room technician : Follow with **Nesti4™**
   Detection of machines of interest when **thresholds are exceeded**

   If exceeded

2. Control room technician: Indicator **trend analysis**

   If uptrend

3. Expert: Signal analysis and **diagnostics**

   If fault detected

4. Factory: Maintenance action

SMART EXCEPTION : Why ?

- High human expert workload required to guarantee 100% detection
  - No AI to help (neither detect and diagnose)
  - On line : Many machines / High rate of measurements
  - A lot of time wasted in browsing healthy equipments !
  - Risk of missing a fault !

- Attempt
  - Take advantage of huge amount of data (on line)
  - Reduced human workload with automation (systematic browsing)
  - Help human expert to start detailed analysis
  - **100% detection rate**

- Approach

Detect any change in equipment behavior
(from high dimensional multivariate inputs)

Human expert then may focus in confirming and diagnose …

2 Method

SMART EXCEPTION : Basic principle

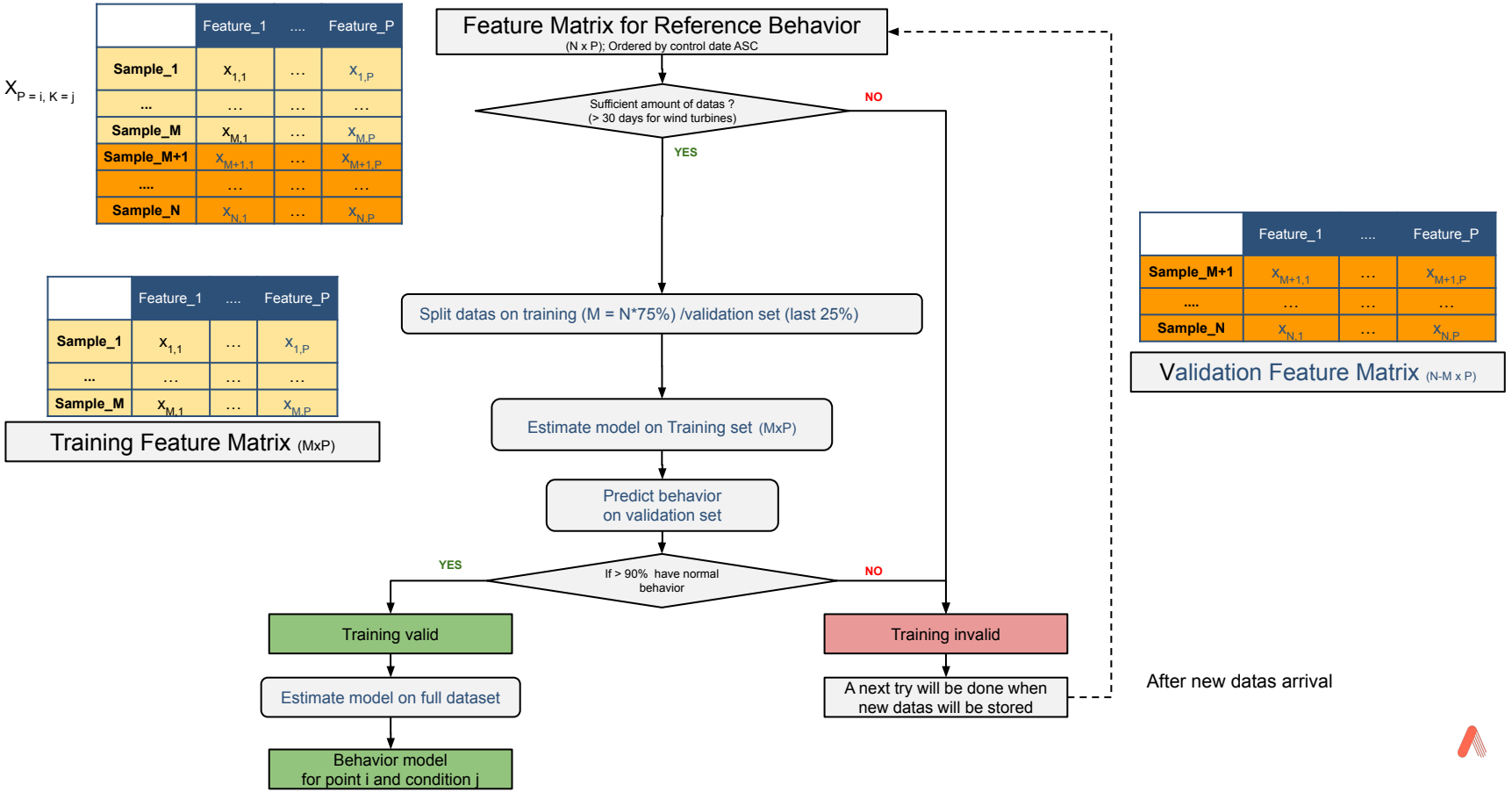
- Step 1 : **Learn the reference (healthy) behavior**
  - Human expert in parallel
  - Or historical data
- Step 2 : **Automatically stop the learning**
  - No threshold, no predefined duration
  - Fully automatic
- Step 3 : **Predict**
  - Raise an alert as soon as behavior becomes too far from reference
  - Human expert diagnosis

A semi-supervised approach !

➢ Need a reference period or a first diagnose

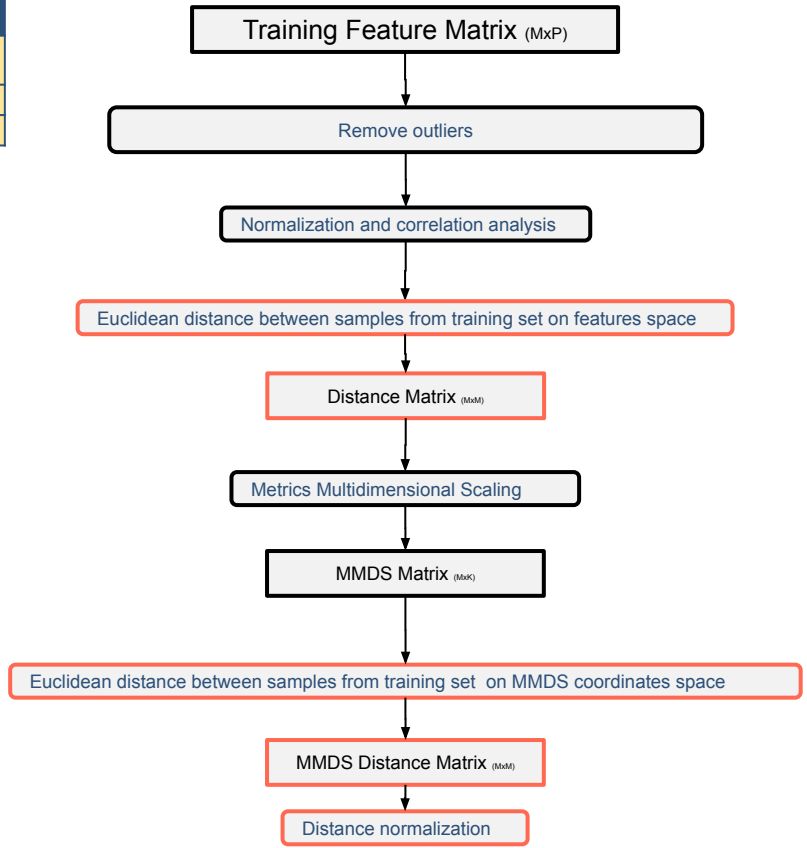
➢ Need relevant features designed by experts

Process to learn model for a specific point/condition



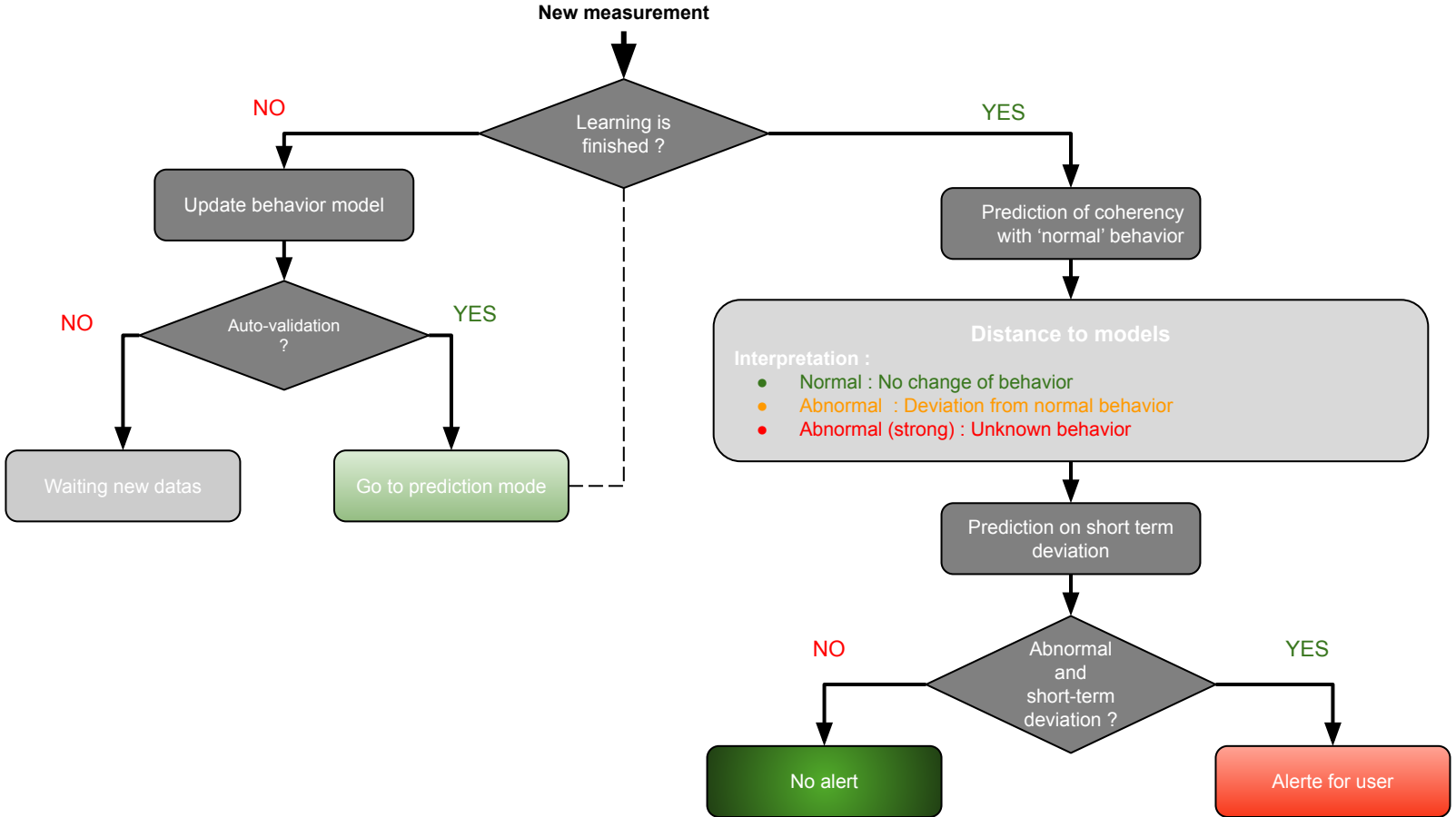
Behavior model from Training set

	Feature_1	....	Feature_P
Sample_1	$x_{1,1}$	…	$x_{1,P}$
...	…	…	…
Sample_M	$x_{M,1}$	…	$x_{M,P}$



1. Data preparation
2. Distance estimation between samples from training set
3. MMDS space definition
4. Distance estimation between samples on MMDS space

SMART EXCEPTION : Survey Process

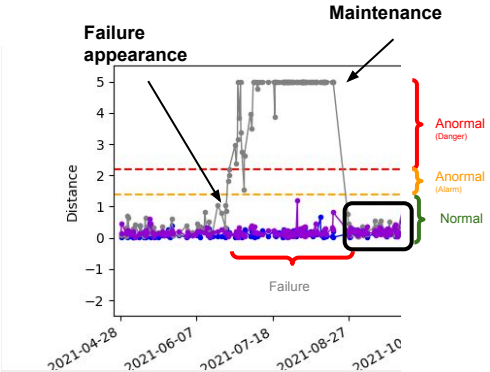


Our output : An unique feature which is the distance to normality

Evolution of distance at normal behavior

- **More distance is high -> more the behavior is different**

Wind turbine



- Component with corrected failure **with get back to normal behavior**
- Component with normal behavior
- Component with normal behavior

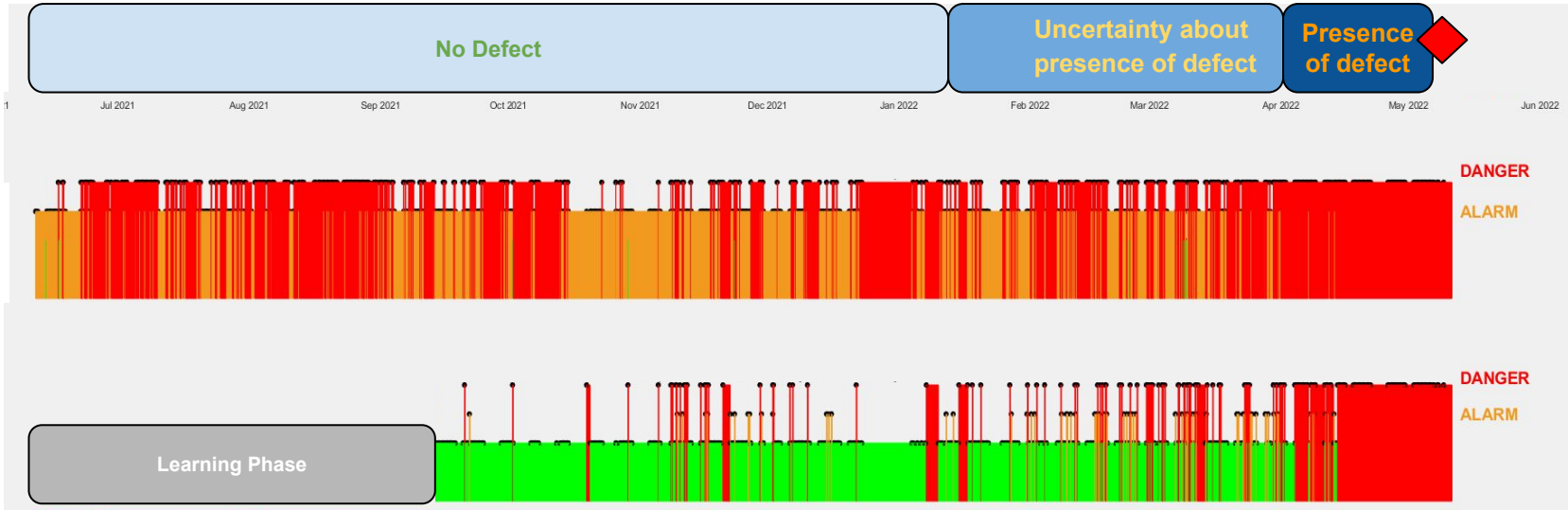
3 Example & Results

Stamping Press Example

Evolution of alarm states over time (Method Comparison)

Failure

Machine Status (Truth)

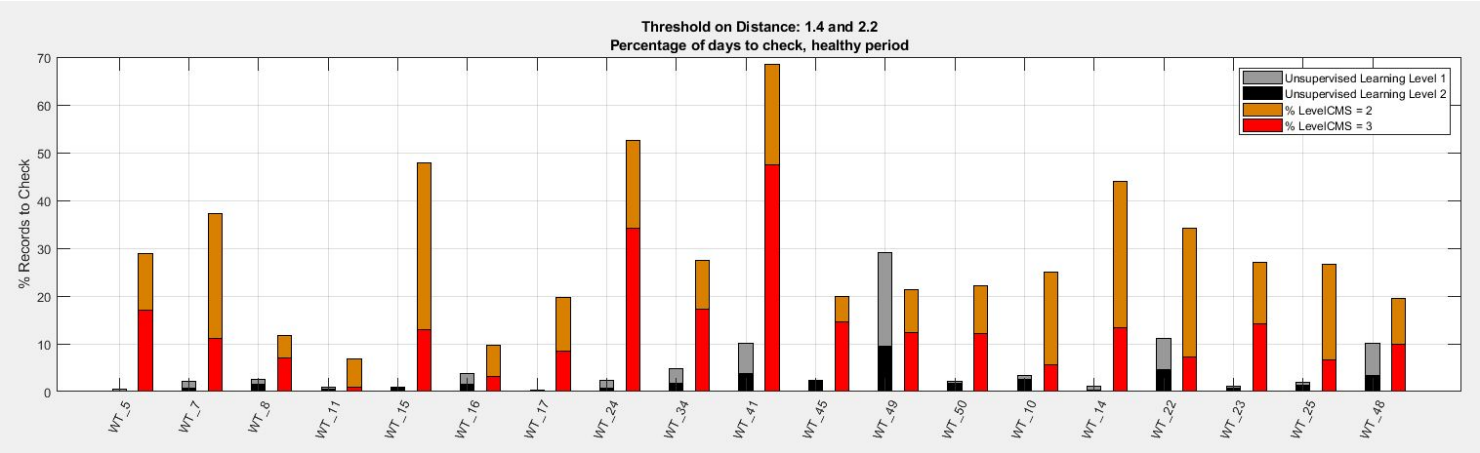


Current Method *(Human Based)*

New Method Proposed *(Data Driven)*

Legend:
Black dots represent measurement dates
(the alarm state is refreshed at each new measurement date)

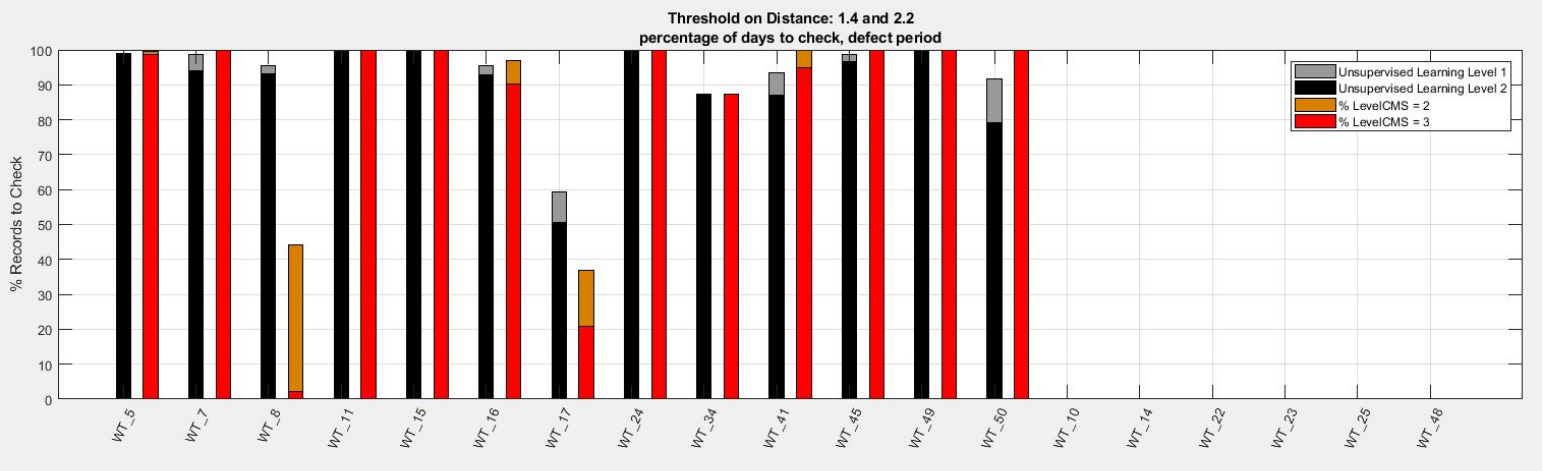
Comparison with thresholds method : False alarm rate



	Number of days with alarm
CMS	7177(40.3%)
ML	1533 (8.6%)
Truth	**17814**

- Reduces the number of false alarms by a factor of 4, regardless of severity
- This brings us to 1 false alarm per month per equipment and measuring point (within the scope of our analysis), compared with an average of 1 per week.

Comparison with thresholds method : Detection and reactivity



Reactivity

Wind turbine	5	7	8	11	15	16	17	17	24	34	41	45	45	49	50
Seuillage CMS	<= 7j	<= 3j	-	<= 3j	<= 15j	<= 7j	<= 15j	<= 3j	<= 3j	<= 15j	<= 3j	<= 15j	<= 3j	<= 3j	<= 7j
ML	<= 7j	<= 3j	<= 7j	<= 3j	<= 15j	<= 7j	<= 15j	<= 3j	<= 3j	<= 15j	<= 3j	-	<= 3j	<= 3j	<= 7j

- Faults always detected with good period recovery
- No deterioration in term of reactivity

4 False alarm reduction

(work in progress)

SMART EXCEPTION : Basic principle

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- Step 2 : **Automatically stop the learning**
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- Step 3 : **Predict**
  - Raise an alert as soon as behavior becomes too far from reference
  - Human expert diagnosis
- Step 4 : **Improve from feedback**
  - False alarms accounting (reinforcement)
  - Repairs accounting (need for extending the reference model or not)

False alarm reduction by user feedback

- Expert feedback on false alarms is possible

- Each example tagged as normal is integrated into the reference measurement set.
  - No update of the MMDS reference space is allowed (Tagged measure is only projected onto MMDS space)
  - Tagged measure participate only for the determination of distance with new measurement

Stamping Press Example

Evolution of alarm states over time (Method Comparison)

Period	#date	%Alert by ML	%Alert by ML with feedback
No defect (without learning)	697	4.30%	1.72%
Uncertainty	354	28.81%	18.36%
Apperance	74	70.27%	67.57%
Hard	76	100.00%	98.68%
Toal	1201	21.65%	16.82%

FA reduced by 3 on healthy period

No significant reduction in detection rate

5 Perspectives

Perspectives

- Introduce hybridation with Raw input (to avoid lack of pertinence for inputs)
- Improve distance estimation on MMDS space with densities (for greater robustness)
- Make a prediction for the risk of alerts for next measurement

Thanks !