

### **ENTERPRISE INSIGHT and Proactive Analytics**



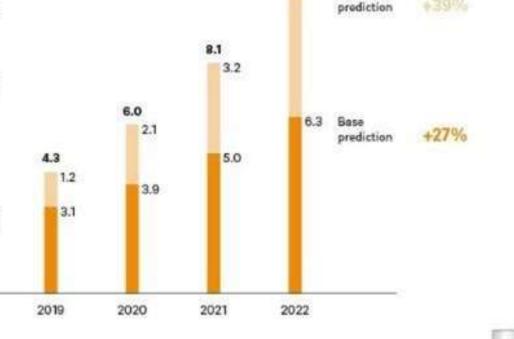
**Predictive Maintenance with Machine Learning Models** 

### **Overview**

- Predictive Maintenance
  - Market trend
  - Physics-Heuristics-ML Models
  - Explanation of problem solved by Machine Learning in Predictive Maintenance (with Advanced Pattern Recognition Models)
  - Probabilistic Diagnostic Model
- Heat Exchanger Analysis through different tools

#### **Predictive Maintenance Market Trend**

We expect the market for Predictive Maintenance to grow by 20 to 40 percent a year across all industries and applications.



Source "Market research future", IoT Analytics, Roland Berger

2016

2017

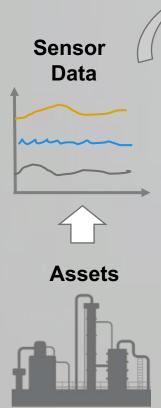
2018



CAGR 2016-2022

Optimistic

# Holistic Approach to Health Monitoring





Physics-based Models: derived from thermodynamic or first principles

"Has the efficiency of the equipment deviated significantly from the design"

Heuristic-based Models: derived from SME or engineering insight:

"Problems happen when temperature is high and pressure is low..." Machine Learning
Models: derived from
a data-driven model
estimation

"Are current vibration measurements normal compared to historical normal operation?..."

#### **Alerts**

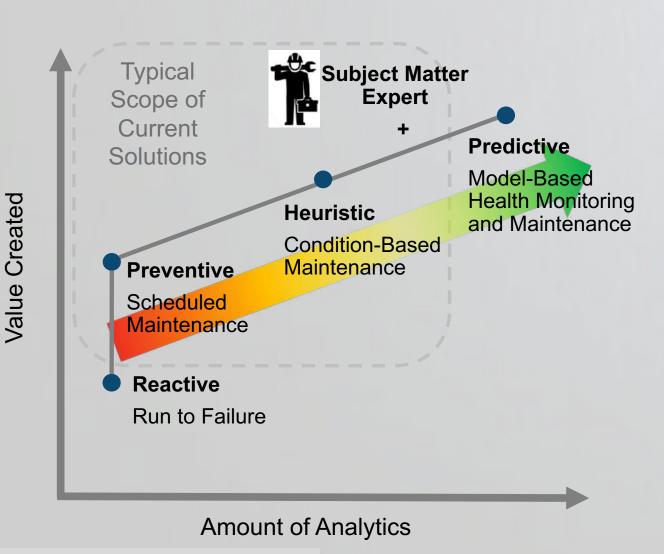
E.g. Compressor efficiency < 90%

E.g. Temp. > Temp. MAX Press. ≤ Press. MIN E.g. Historical Vibration → Data-driven model → Expected Vibration

(Measured – Expected) > Limit

Alert Management Analysis

#### **ASSET HEALTH MONITORING AND DATA ANALYTICS**



**Example: Compressor Bearing** Predictive ML Models Ultrasonic Detection Failure Starts Vibration Detection Oil Analysis Detection Audible Noise **Asset Health** Hot to Touch Mechanically Catastrophic Failure Warning Early Late Time

SPAIN AI 30th April

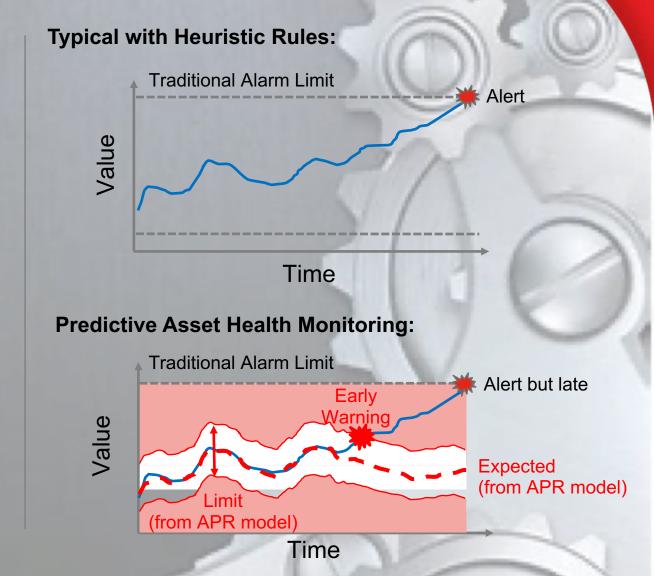
### **ASSET HEALTH MONITORING**

#### **Heuristic Rules:**

 Sensor Alarm limits must be set outside of normal operating range to cover all possible conditions

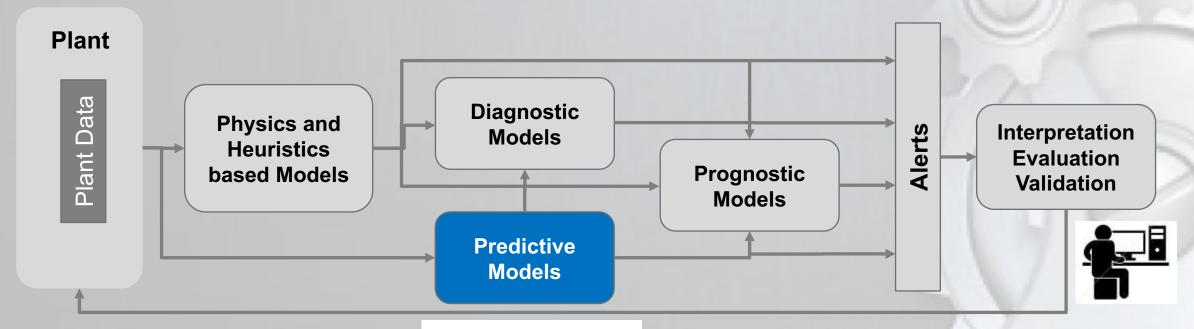
#### **Predictive Asset Health Monitoring:**

- Advanced Pattern Recognition (APR) Machine Learning (ML) trained models
- Compares observed behavior to expected behavior
- Provides early warning of sensor issues and equipment degradation
  - Can determine very subtle condition changes to identify anomalies
- Makes SME aware of abnormal conditions and supports the decision making process



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# Holistic Approach to Health Monitoring



#### **Maintenance Actions**

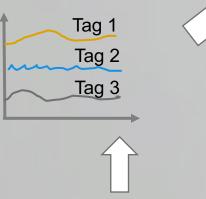


Anomaly Detection with Advanced Pattern Recognition

Advanced data visualization and analytics

# **Asset Health Monitoring with APR Machine Learning**

#### **Historical Data**





# Typical Case Is this normal?

		Ĭ	igh
Tag 1	10	0	100
Tag 2	2	0	100
Tag 3	1.2	0	100



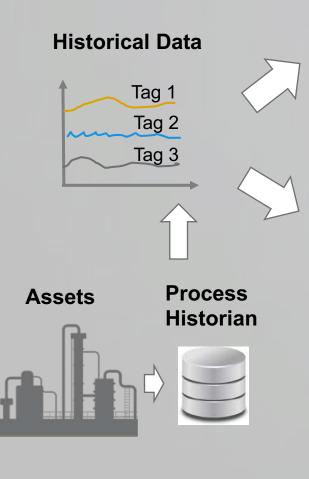
#### **Assets**

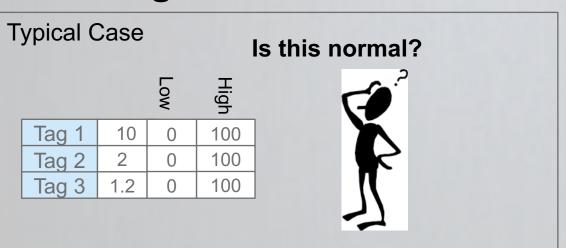


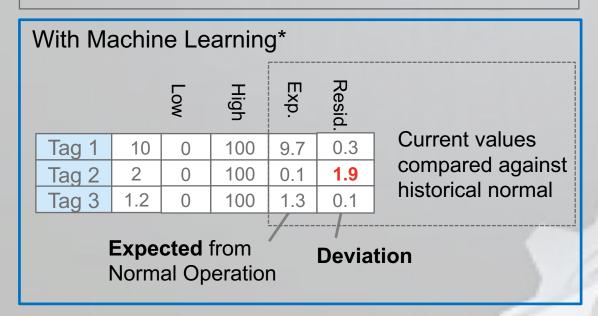
Process Historian



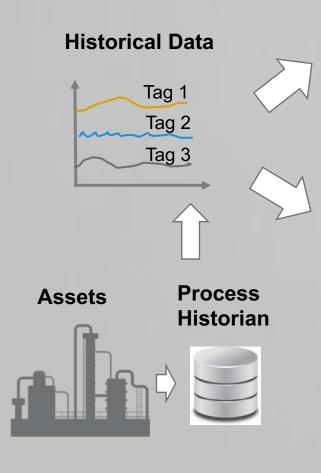
# **Asset Health Monitoring with APR Machine Learning**

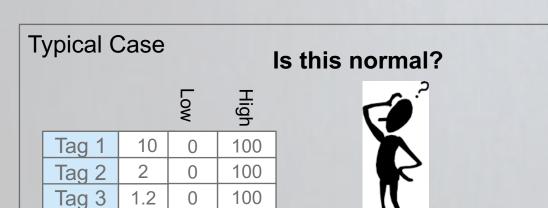


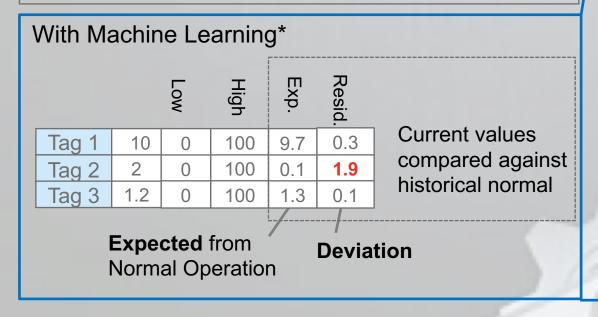




## **Asset Health Monitoring with APR Machine Learning**



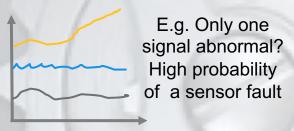




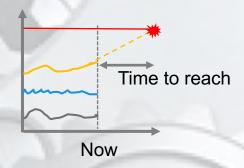
Are the current patterns normal?



Does the pattern indicate a specific failure [Diagnostics]?

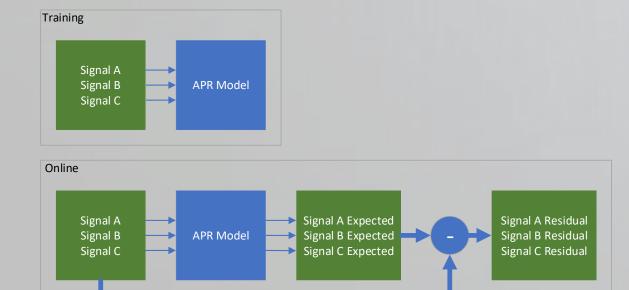


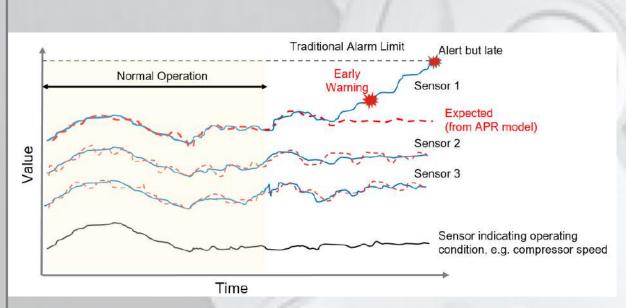
How long before reaches critical limits [Prognostics]?



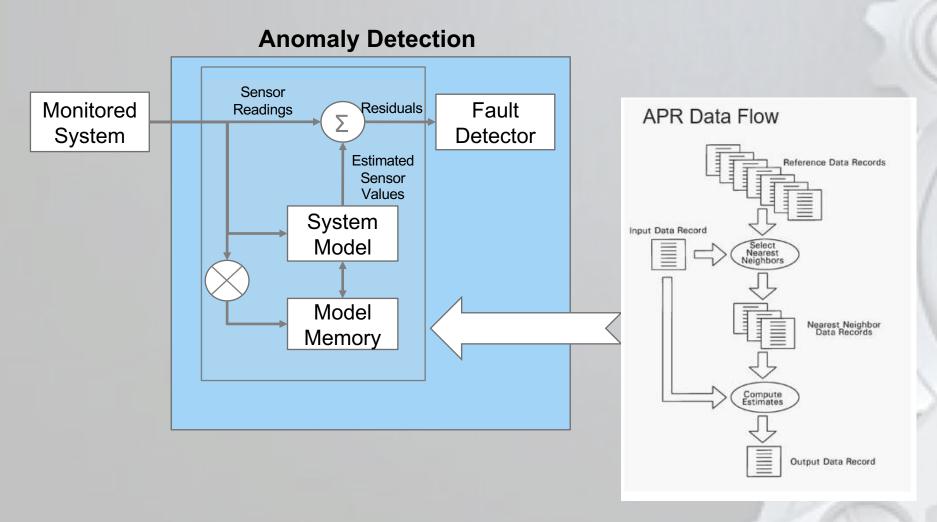
## **APR Modeling: Basic Concepts**

- APR models learn patterns from <u>multiple signals</u> from normal (historical) operation
- Learned patterns include correlation among sensor signals, historical max/min values, correlation with operating conditions



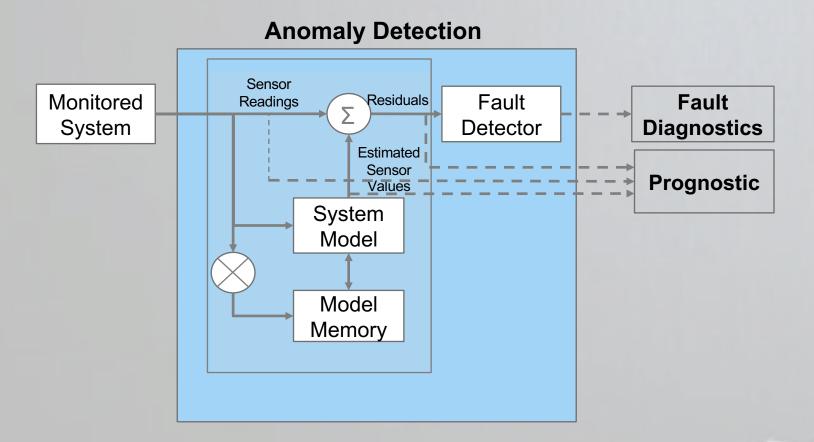


# **Asset Health Monitoring with APR Models: Data Flow**



APR estimates are based on the similarity of a new observation with each of the reference patterns ("Model Memory") An estimate of each input is computed using multi-variate kernel regression over the reference patterns

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# **APR Modeling: Simple Example**

		Historical	Data				
Time	Signal 1	Signal 2	Signal 3	Signal 4		Differer	
0	5	10	7.7	1	Signal 1	_	_
1	5.5	10.6	8.5	1.2	-4.8	-3	-1.
1					-4.3	-2.4	-0.
2	6.3	10.6	8.7	0.8	-3.5	-2.4	-0.
3	7.3	10.9	9.2	0.7	-2.5	-2.1	0.2
4	8.6	11.4	9.9	0.8	-1.2	-1.6	0.9
5	9.8	12.2	10.9	1.2		-0.8	1.9
6	11.5	12.9	11.8	1.5	1.7	-0.1	2.8
7	12.45	14.1	13.2	2.3	2.65	1.1	4.2
8	13.45	14.55	13.85	2.35	3.65	1.55	4.8
9	14.55	15.05	14.55	2.45	4.75	2.05	5.5
10	16.15	15.65	15.35	2.65	6.35	2.65	6.3
11	17.15	16.75	16.65	3.35	7.35 8.35	3.75 4.25	7.6 8.3
12	18.15	17.25	17.35	3.45	, to .33	7.20	0.5

	Differen	ce Data		Sum
Signal 1	Signal 2	Signal 3	Signal 4	Sum(  )
-4.8	-3	-1.3	-0.9	10
-4.3	-2.4	-0.5	-0.7	7.9
-3.5	-2.4	-0.3	-1.1	7.3
-2.5	-2.1	0.2	-1.2	6
-1.2	-1.6	0.9	-1.1	4.8
0	-0.8	1.9	-0.7	<mark>3.4</mark>
1.7	-0.1	2.8	-0.4	5
2.65	1.1	4.2	0.4	8.35
3.65	1,55	4.85	0.45	10.5
4.75	2.05	5,55	0.55	12.9
6.35	2.65	6.35	0.75	16.1
7,35	3.75	7.65	1.45	20.2
8.35	4.25	8.35	1.55	22.5

Minimum Difference

	Measi	urement	
Signal 1	Signal 2	Signal 3	Signal 4
9.8	13	9	1.9

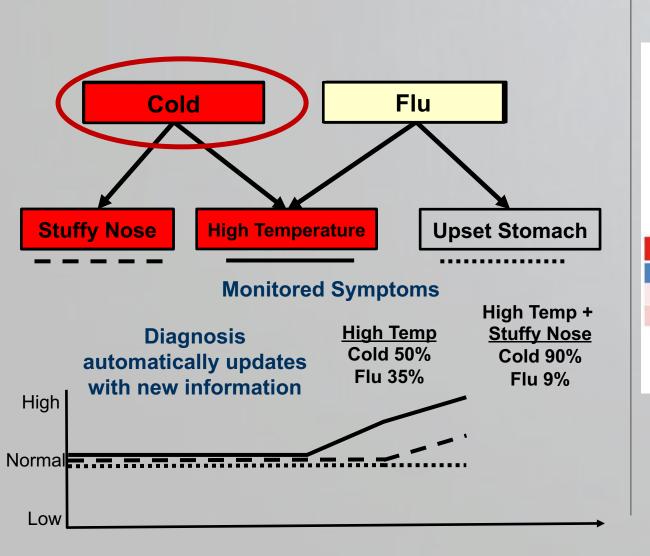
	E	xpected	
Signal 1	Signal 2	Signal 3	Signal 4
9.8	12.2	10.9	1.2

This is a simple version of a similarity-based APR algorithm

### **Probabilistic Diagnostic Model: Introduction**

- Diagnostic models capture asset operating expertise
  - Brings expertise online
  - Combines results from multiple detection models
- Diagnostics model use a Bayesian belief network (BBN) driven from fault detector events
  - Best approach for complex failure modes with overlapping symptoms
- Diagnostic model helps to determine the likehood of a sensor, asset, or model problem.
  - Alternatives are rule-based models or SME experience to understand individual or groups of alerts

## **Example of Probabilistic Diagnostic Model**



#### **Configuration:**

90%

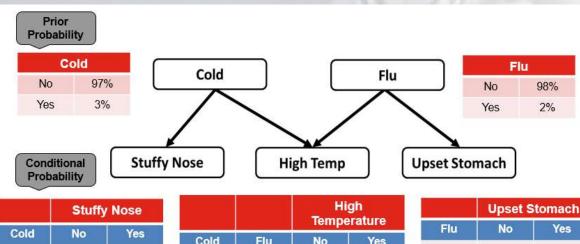
10%

No

Yes

10%

90%



		Temperatur			
Cold	Flu	No	Yes		
No	No	99%	1%		
Yes	No	10%	90%		
No	Yes	5%	95%		
Yes	Yes	99%	1%		

	Upset Stomach		
Flu	No	Yes	
No	90%	10%	
Yes	10%	90%	

## **ASSET DESCRIPTIVE MODEL (Heat Exchanger)**

>Descriptive analytics: Observed relationships and trends among different variables identifying several patterns

- Flow Mode
- Shutdown Mode

**Delta Water Temperature** 

Brown: Air In Flow

Green: Delta Air

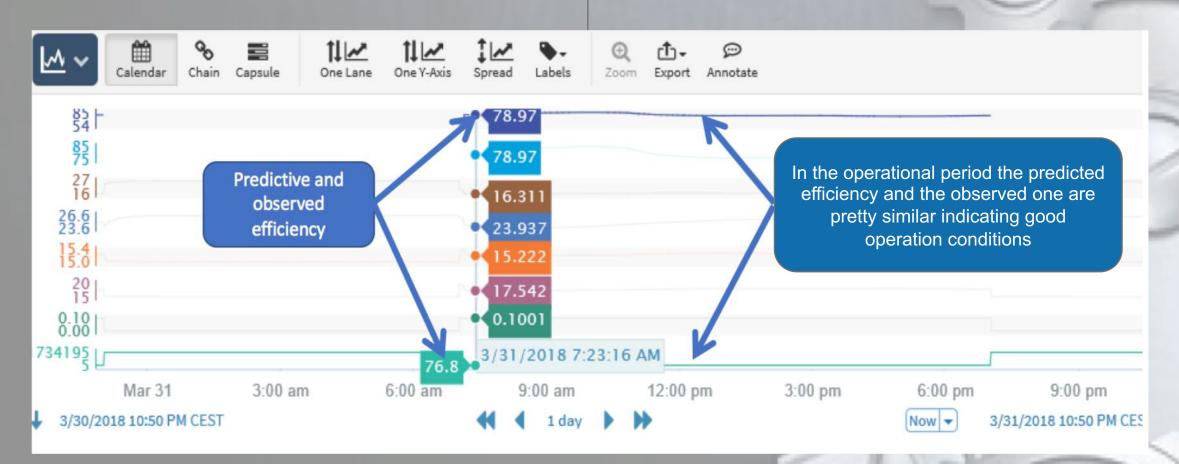
**Violet: Water Inlet Flow** 

Pink: Efficiency



## **ASSET PREDICTIVE MODEL (Heat Exchanger)**

➤ Predictive analytics: Create basic regression models to compare the observed operation with the predictive operation which is generated through regressions models taking "efficiency" as dependent attribute



#### **HEAT EXCHANGER**

It has been simulated through 3 modeling methods:

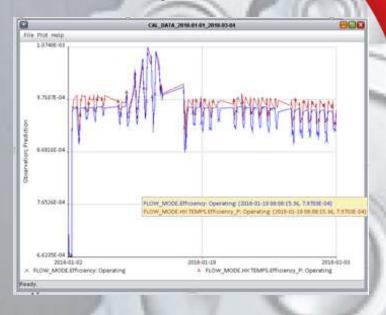
▶ Prediction Step: Involve the use of models describing the asset when it is operating correctly to estimate the expected values of the observed data from the asset. (APR Modeling)

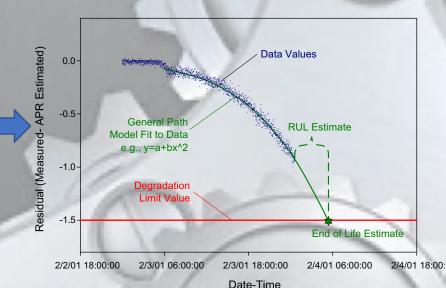


➤ Diagnosis Step: Correlates this pattern of agreement or disagreement with the most likely problem cause or abnormal state of the asset. Bayesian Belief Network (BBN) run it

▶ Prognosis Step: Finally, the evolving diagnosis and condition data to determine the residual use life (RUL) to act before a service interruption happen using a quadratic function a+bx² modeled with 100 points being the degradation limit selected 2°C for the Air Temperature out

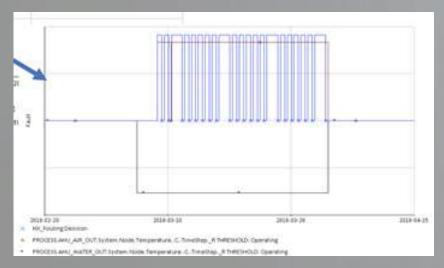
#### Efficiency





### **EXAMPLE HEAT EXCHANGER DIAGNOSIS AND PROGNOSIS**

#### **Diagnosis Fouling scenario**



- ✓ Water Out Temperature 
  →

Conclusion: Fouling starts with the combination of both conditions

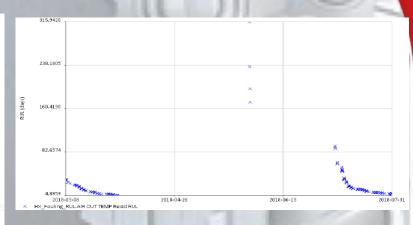
#### **Diagnosis Leaking scenario**



- ✓ Water Out Temperature →
- ✓ Water In flow

Conclusion: Leakage starts when the Water in flow fall down

#### **Prognostic Fouling scenario**



- ✓ Water Out Temperature 
  →

Conclusion: RUL is pretty similar in the two fouling scenarios simulated in March 18 and July 2018

