On the Use of Artificial Intelligence-based Modeling of Sensor Networks in Energy Systems

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invited speech by eurolab

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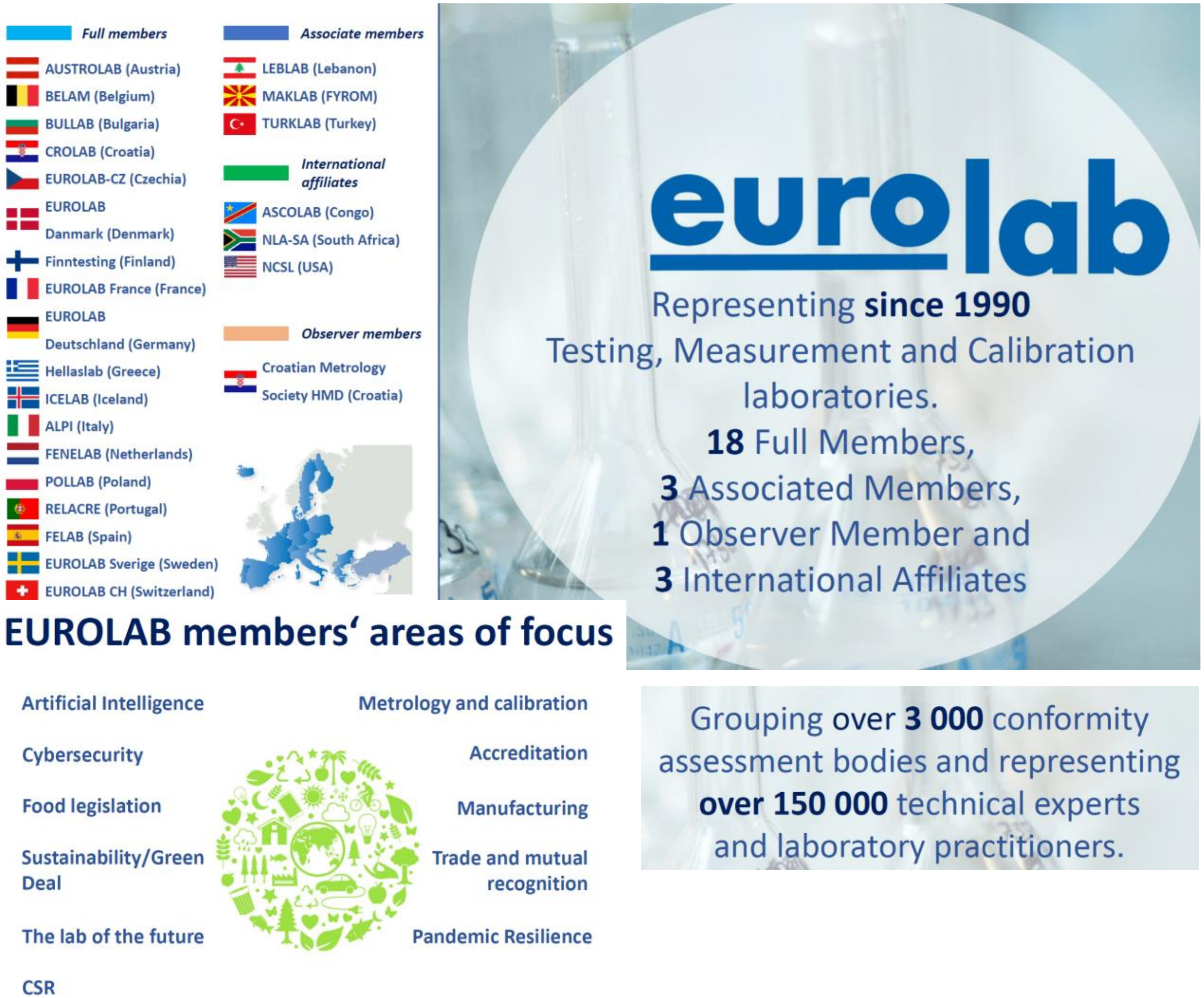
I like work: it fascinates me, I can sit and look at it for hours

Jerome K. Jerome, "Three Men in a Boat", 1889

In collaboration with Fabrizio Bonacina, Eric Stefan Miele

Team for *Artificial Intelligence* in Complexity Modeling



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Contents

Start with why … *challenges*

Industry 4.0 key paradigm is about linking operations - in industry (and energy) - and ICT to make production more flexible

Industrial metrology is the enabling factor to empower individualized products as instrumental to process adjustment

production facilities are frequently *reconfigured*/or *adapted*

associated *changes in production control operations* must be implemented efficiently to survive permanently in the market

Industrial metrology is creating/capturing a map of real world (digital twin) virtual planning model

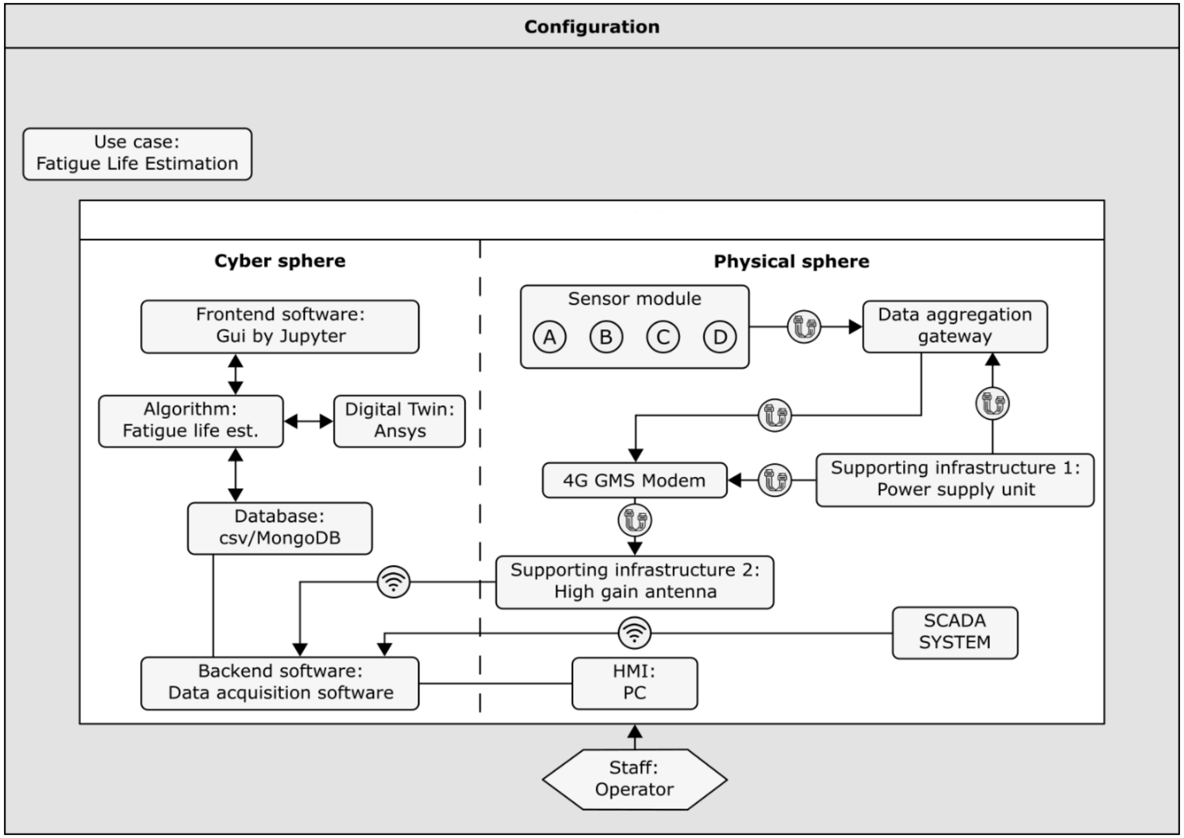
Data collected constitute a central component of **cyber-physical (production) systems** (aka CPPSs) which aim at lifting the current productivity limitations of established processes and meeting the requirements of operability and networkability

Start with why … *CPPS*

E.A. Lee et al. (2006):
«Integration of computation with physical processes»

R. Rajkumar et al. (2012):
«physical and engineered systems whose operations are monitored, coordinated, controlled, and integrated by a computing and communication core»

V. Gunes et al. (2014):
«a term describing a broad range of complex, multidisciplinary, physically-aware next generation engineered system that integrates embedded computing technologies (cyber part) into the physical world»



* Reference architecture by Sascha Julian Oks et al. (2019)

Start with why … challenges

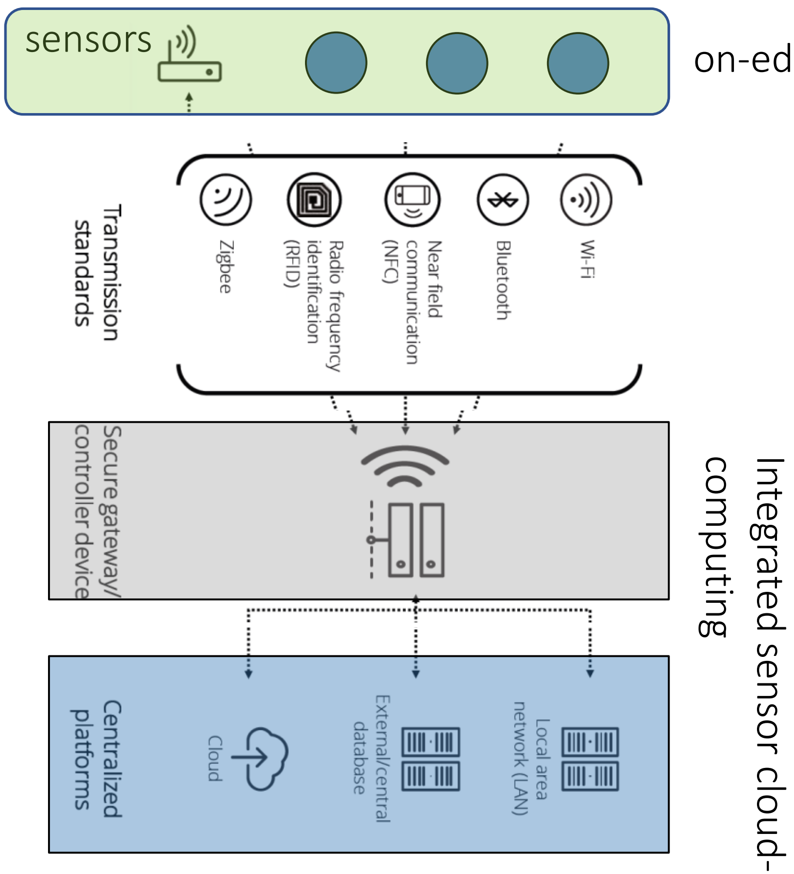
Integrating sensor, measurement technology and data analytics (IIoT) is thus a key element in the success of CPPS

Such integration must advocate the following goals

i. collecting the “right” measurement data
ii. at the “right” place, and
iii. time,
iv. manageable to process intelligence (form collected data have has a decisive influence on the quality of any derived index or indicator),
v. sensor layer must also react robustly to redundant and conflicting data (resilient production in a resilient factory perspective)

Industrial metrology challenges/trends are *fastness*, *accuracy*, *reliability*, *flexibility* and *holistic (using sensor networks rather than sensor signals)*

Start with why … *IIoT challenges*

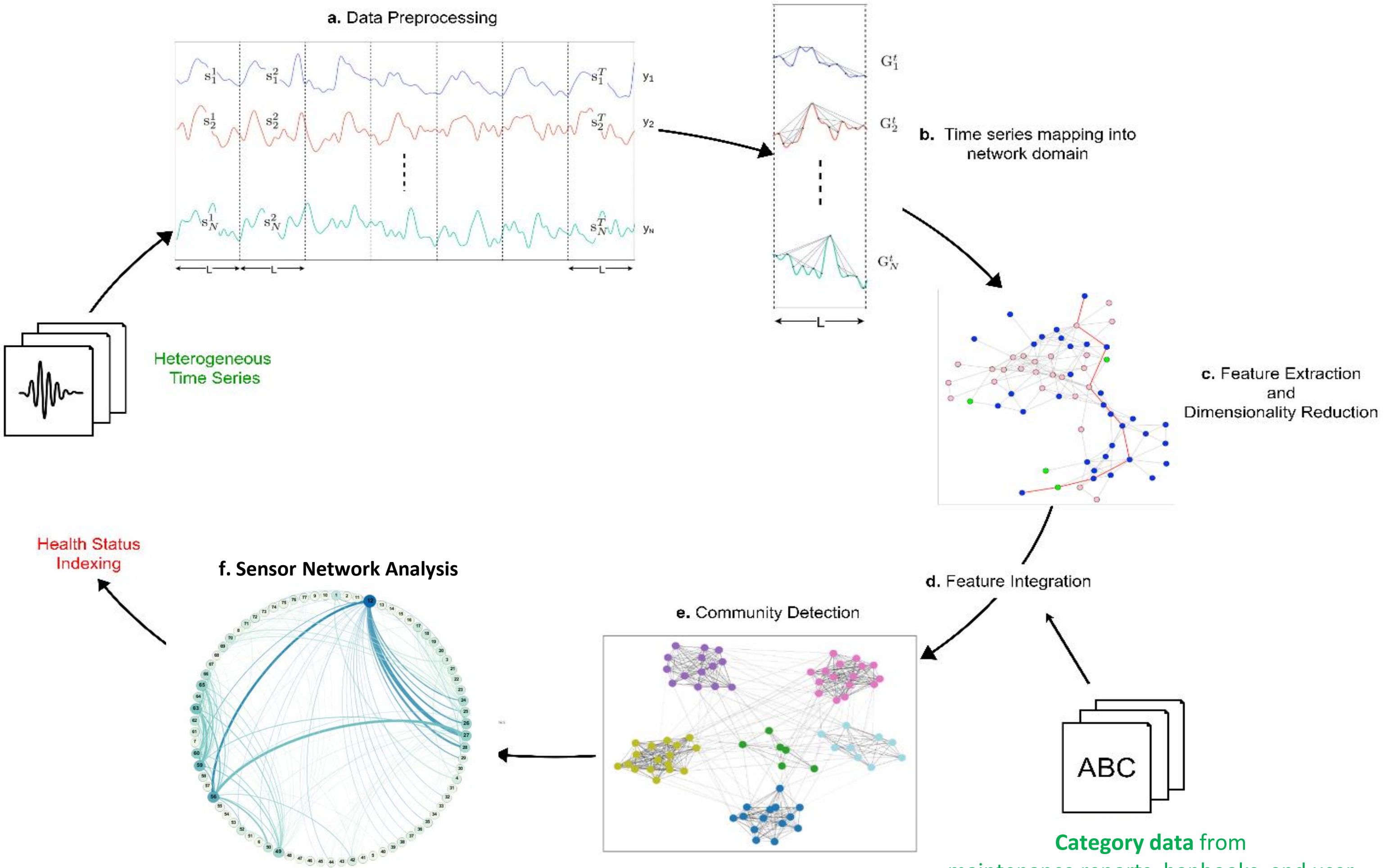


Metabolic dynamic mapping and hidden correlation unveiling

KPI identification in genuine Multi-Variate environments and complex engineering (eco)systems

Datafication for the O&M (Predictive and Prescriptive)

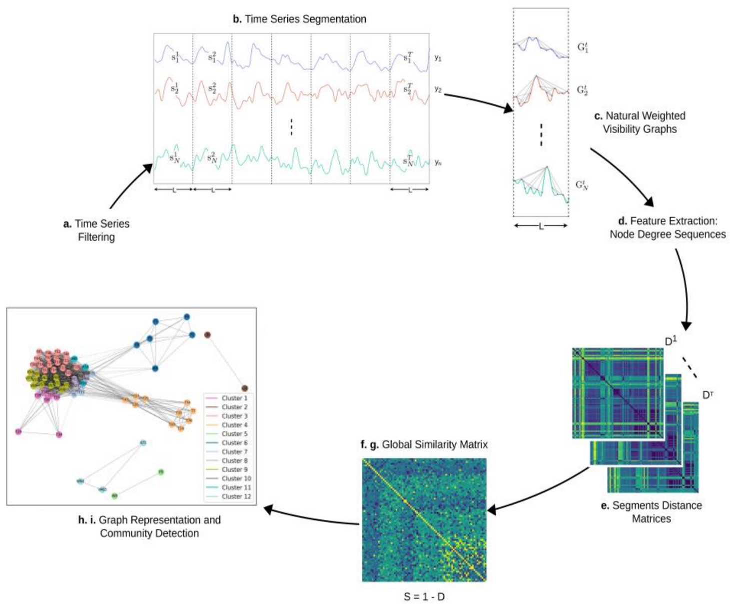
Methodology, *Sensor Network Analysis*



Category data from maintenance reports, hanbooks, end user attributes, etc.

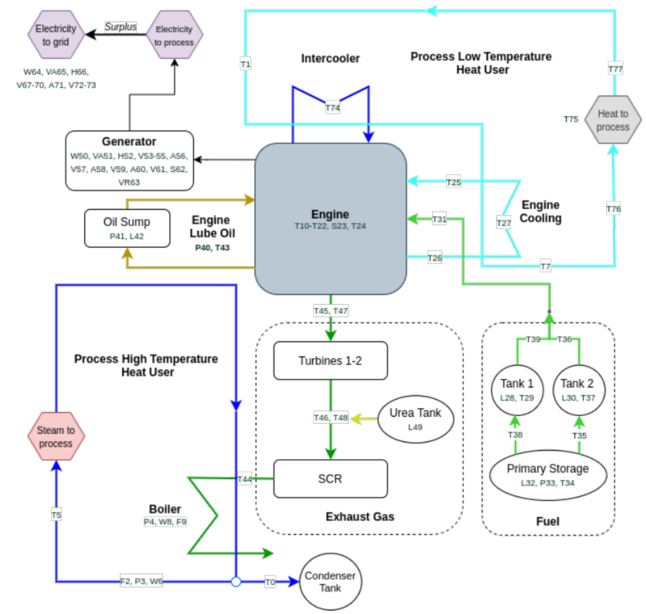
Methodology (2)

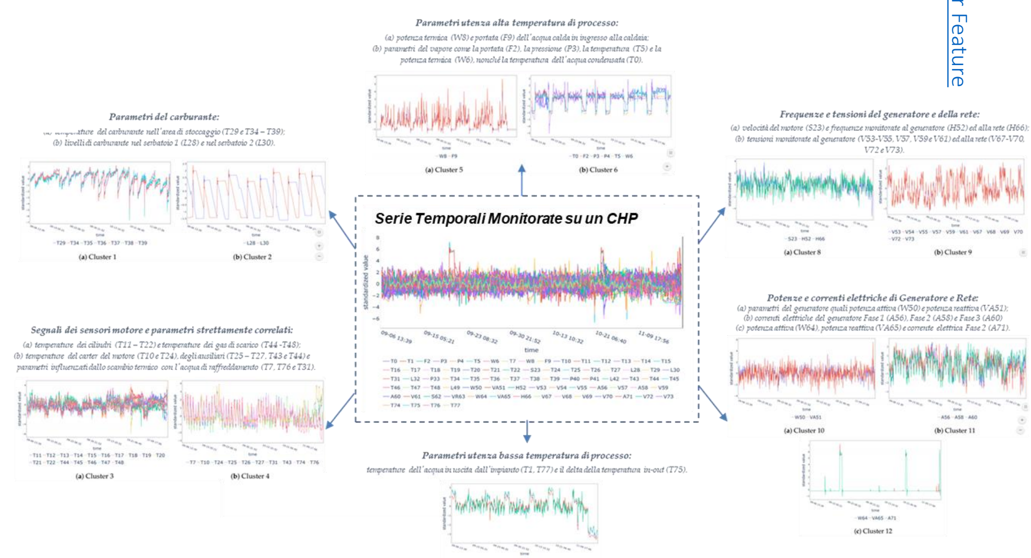
Time Series Clustering: A Complex Network-Based Approach for Feature Selection in Multi-Sensor Data



Unsupervised FSS algorithm based on a novel feature clustering technique tailored to time series in industrial IoT sensor networks.

Clustering complements **visibility graphs** to map time series in the network domain, node **degree sequences** extraction to characterize them, and **community detection** algorithms to perform time series clustering





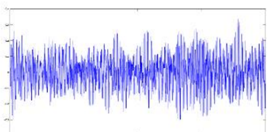
Groups of Similar Time Series

[Time Series Clustering: A Complex Network-Based Approach for Feature Selection in Multi-Sensor Data](#)F Bonacina, ES Miele, A Corsini
Modelling 1 (1), 1-21

Methodology (3)

For this purpose we have defined an **unsupervised** approach for data labeling based on complex network measurement, in order to also include the precursor phenomena. At the end of this phase all the faults and anomalies identified were then compared and validated with the events included in the maintenance reports

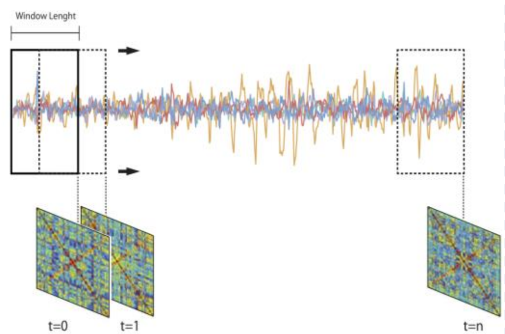
Time Series (Sensors Signals)

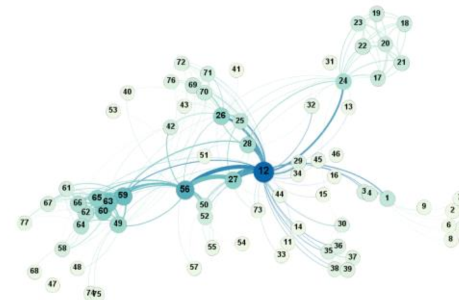


1. Normalization (Standard Scaler)

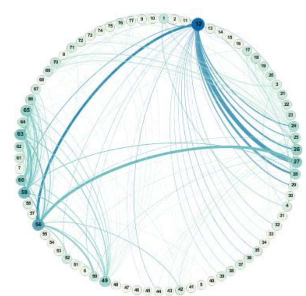
2. Connectivity Analysis

Window Lenght: 6 h
Overlap: 3 h





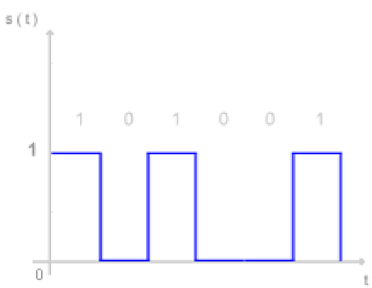
3. Graph Modeling (Dynamical Networks)



4. Complex Network Analysis:

- Node Weighted Degree Centralities,WDC

5. CUSUM Chart based on Node WDC



6. Binary Data Labeling:

- Class 0: Standard Operation;
- Class 1: Prefault

Complex Network Analysis of Photovoltaic Plant Operations and Failure Modes
F Bonacina, A Corsini, L Cardillo, F Lucchetta, Energies 12 (10), 1995

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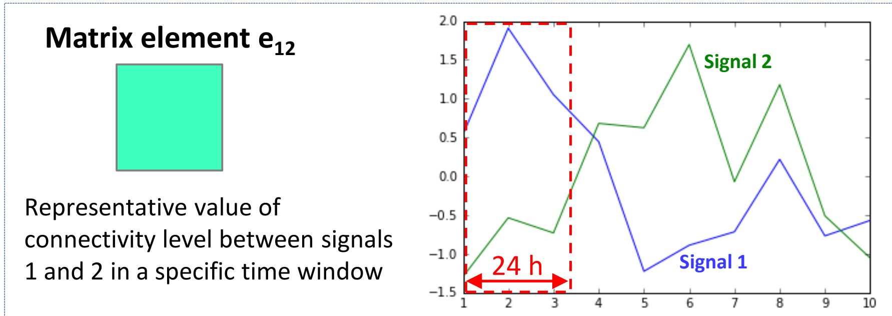
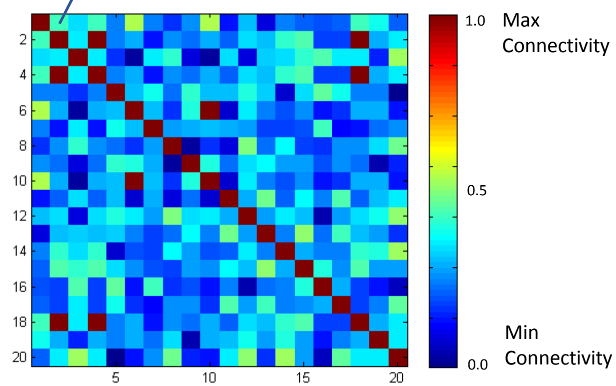
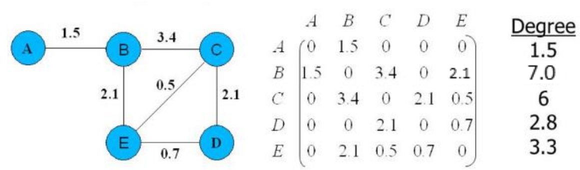
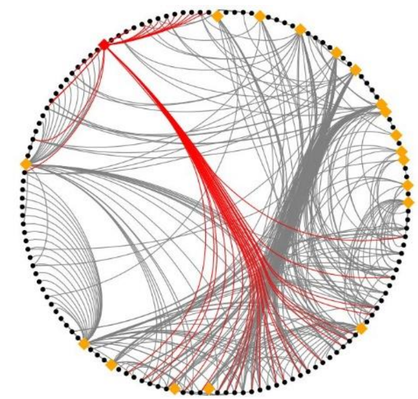
Methodology (4)









Connectivity Matrix

Adiacency matrix (nxn where n is the number of monitored parameters) associated with each temporal window of fixed lenght. Each element e_{ij} represents the existing relation between variables *i* and *j* and it is visualized through the color variation.

Complex Network Metrics: *Total Degree*

It is a centrality measurement. Centrality is directly related to te potential importance of a node (variable) in the graph.

$$\mathbf{WDC} = \sum_{j=0}^{N} w_{ij}$$

where w_{ij} is the weight of the edges connected to the node *i*.

Visual Analytics: *Circular Layout*

Nodes are positioned along a circumference and are ranked based on node metric.

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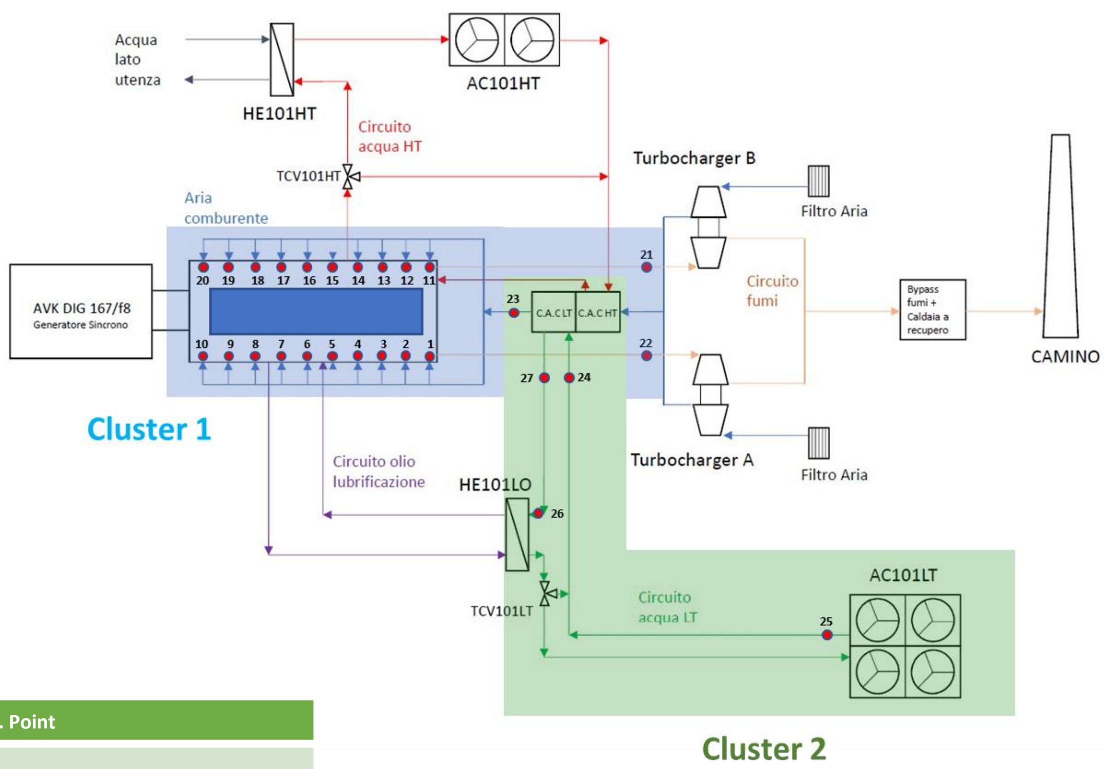
Fault prognosis in multi-MW ICE gen-set

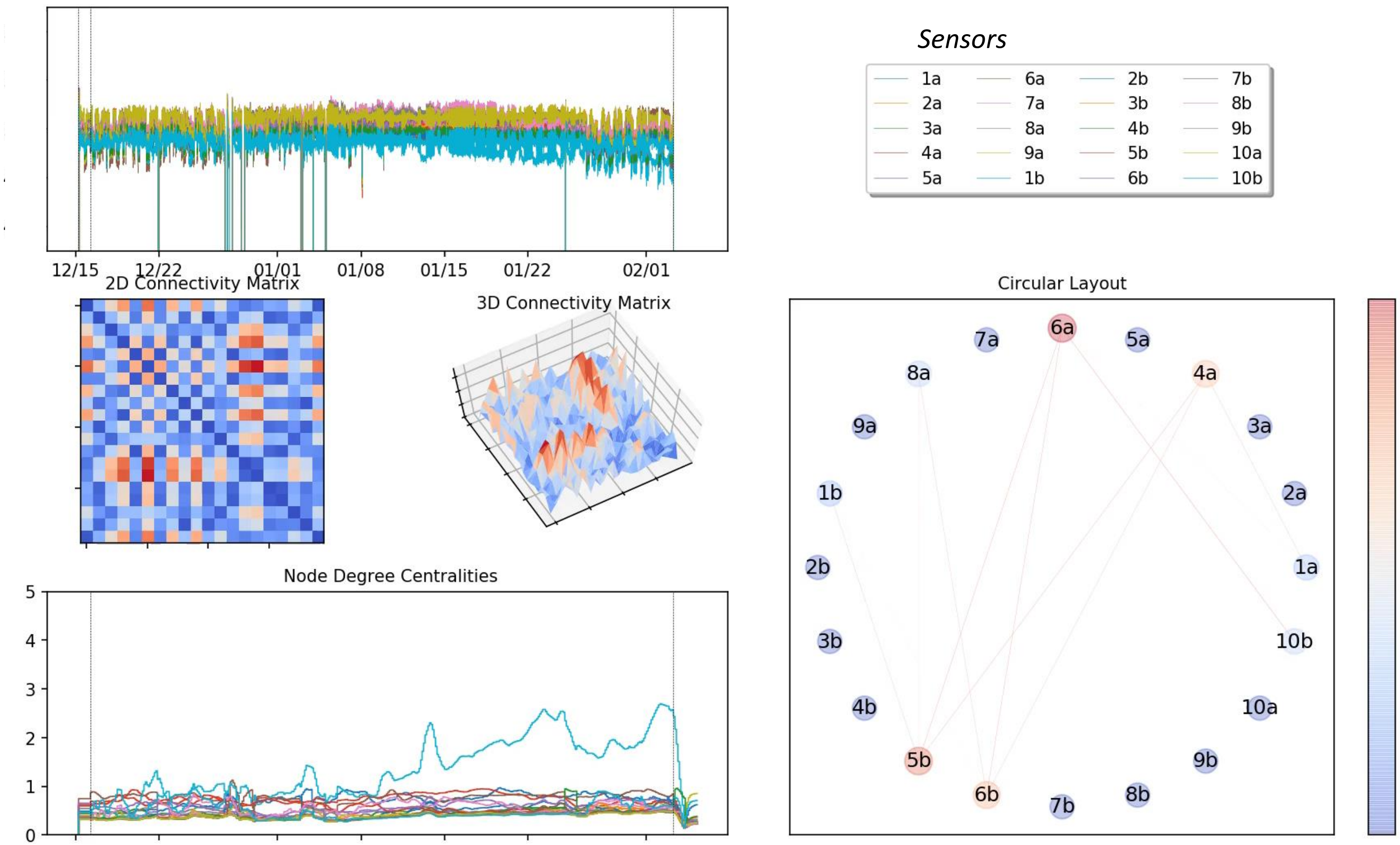
Sensor networks and clustering

Parameter ID	Description	Mis. Point
Ex_1a_F	Cylinder 1A Temperature (°C)	1
Ex_2a_F	Cylinder 2A Temperature (°C)	2
Ex_3a_F	Cylinder 3A Temperature (°C)	3
Ex_4a_F	Cylinder 4A Temperature (°C)	4
Ex_5a_F	Cylinder 5A Temperature (°C)	5
Ex_6a_F	Cylinder 6A Temperature (°C)	6
Ex_7a_F	Cylinder 7A Temperature (°C)	7
Ex_8a_F	Cylinder 8A Temperature (°C)	8
Ex_9a_F	Cylinder 9A Temperature (°C)	9
Ex_10a_F	Cylinder 10A Temperature (°C)	10
Average_A_F	Average Cylinder's A Temperatures (°C)	-
Ex_1b_F	Cylinder 1B Temperature (°C)	11
Ex_2b_F	Cylinder 2B Temperature (°C)	12
Ex_3b_F	Cylinder 3B Temperature (°C)	13
Ex_4b_F	Cylinder 4B Temperature (°C)	14
Ex_5b_F	Cylinder 5B Temperature (°C)	15
Ex_6b_F	Cylinder 6B Temperature (°C)	16
Ex_7b_F	Cylinder 7B Temperature (°C)	17
Ex_8b_F	Cylinder 8B Temperature (°C)	18
Ex_9b_F	Cylinder 9B Temperature (°C)	19
Ex_10b_F	Cylinder 10B Temperature (°C)	20
Average_B_F	Average Cylinder's B Temperatures (°C)	-
EX_T_BF_TURBO_B_F	Turbocharger B Inlet Temperature (°C)	21
EX_T_BF_TURBO_A_F	Turbocharger A Inlet Temperature (°C)	22



Parameter ID	Description	Mis. Point
CA_TEMP_F	Supercharging Air Temperature (°C)	23
LT_W_TEMP_INLET	Cooling Water Temperature at Engine Inlet (°C)	24
TT06LT	Cooling Water Temperature at Engine Inlet (°C)	24
TT103LT	Cooling Water Temperature at Air Cooler Outlet (°C)	25
TT106LT	Cooling Water Temperature at Oil Cooling Exchanger Outlet(°C)	26
TT102LT	Cooling Water Temperature at Engine Outlet (°C)	27

Fault prognosis in multi-MW ICE gen-set



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Predicting operations in Multi-MW HAWT

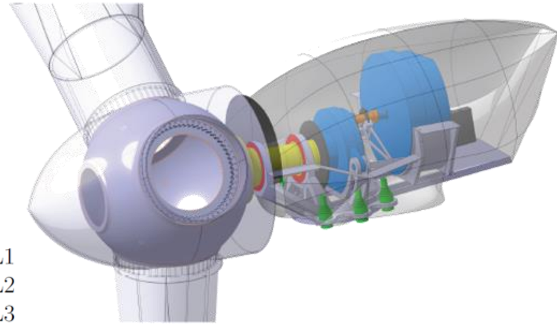
Data is collected from a wind farm consisting of five WTs, each with a rated power of 2 MW
Wind farm is ranked as class 2 according to the standard IEC 61400

EDP. Wind Farm 1 - Failures, 2016. Data retrieved from EDP Open Data, https://opendata.edp.com/ 396 explore/dataset/htw-failures-2016/information/.

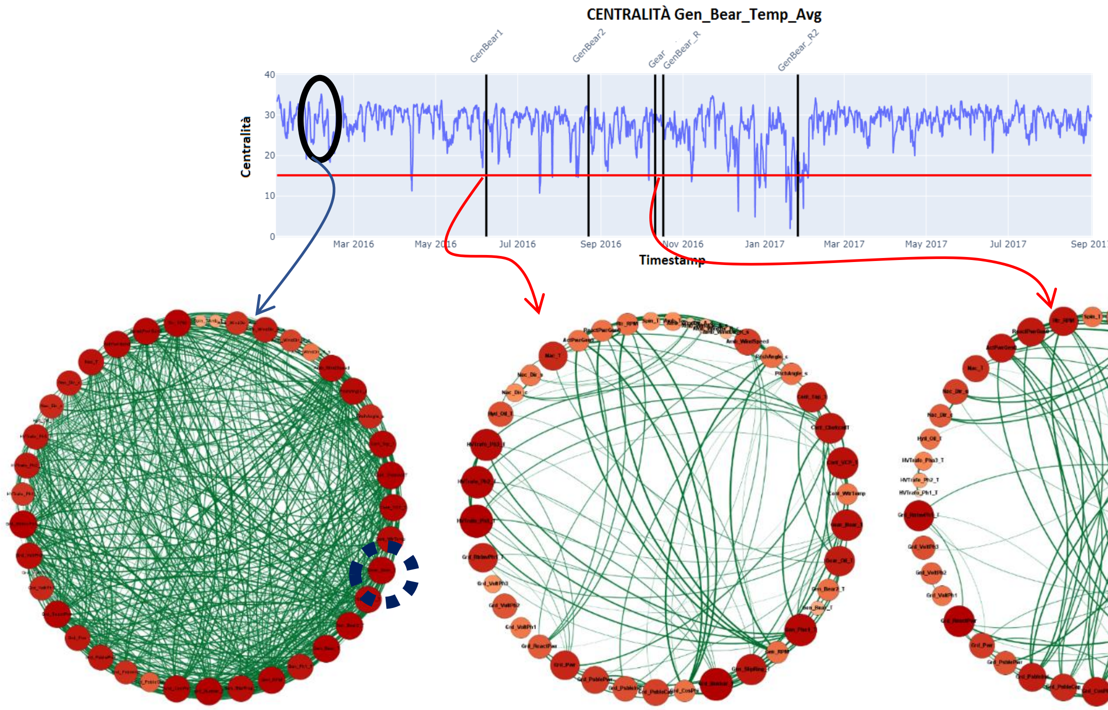
Table 1: Technical information of each turbine.

Rated power (kW)	2000
Cut-in wind speed (m/s)	4
Rated wind speed (m/s)	12
Cut-out wind speed (m/s)	25
Rotor diameter (m)	90
Rotor swept area (m^2)	6362
Number of blades	3
Max rotor speed (rpm)	14.9
Rotor tip speed (m/s)	70
Rotor power density 1 (W/m^2)	314.4
Rotor power density 2 (m^2/kW)	3.2
Gearbox Type	Planetary/spur
Gearbox stages	3
Generator type	Asynchronous
Max generator speed (rpm)	2016
Generator voltage (V)	690
Grid frequency (Hz)	50
Hub height (m)	80
Tower Type	Steel tube
Tower Shape	Conical
Tower corrosion protection	Painted

Signal ID	Description
Gen_Bear_Temp	Temperature in generator bearing 1 (Non-Drive End)
Gen_Bear2_Temp	Temperature in generator bearing 2 (Drive End)
Gen_RPM	Generator rpm
Gen_Phase1_Temp	Temperature inside generator in stator windings phase 1
Gen_Phase2_Temp	Temperature inside generator in stator windings phase 2
Gen_Phase3_Temp	Temperature inside generator in stator windings phase 3
Gen_SlipRing_Temp	Temperature in the split ring chamber
Hyd_Oil_Temp	Temperature oil in hydraulic group
Gear_Oil_Temp	Temperature oil in gearbox
Gear_Bear_Temp	Temperature in gearbox bearing on high speed shaft
Nac_Temp	Temperature in nacelle
Nac_Direction	Nacelle direction
Rtr_RPM	Rotor rpm
Amb_WindSpeed	Wind speed
Amb_WindDir_Relative	Wind relative direction
Amb_WindDir_Abs	Wind absolute direction
Amb_Temp	Ambient temperature
Prod_TotActPwr	Total active power
Prod_TotReactPwr	Total reactive power
HVTrafo_Phase1_Temp	Temperature in HV transformer phase L1
HVTrafo_Phase2_Temp	Temperature in HV transformer phase L2
HVTrafo_Phase3_Temp	Temperature in HV transformer phase L3
Cont_Top_Temp	Temperature in the top nacelle controller
Cont_Hub_Temp	Temperature in the hub controller
Cont_VCP_Temp	Temperature on the VCP-board
Cont_VCP_ChokcoilTemp	Temperature in the choke coils on the VCS-section
Cont_VCP_WtrTemp	Temperature in the VCS cooling water
Spin_Temp	Temperature in the nose cone
Blds_PitchAngle	Blades pitch angle



Predicting operations in Multi-MW HAWT



SCADA-based characterization of normal operation

SCADA-based characterization of faults

Fault early identification (<u>generator</u>) using Sensor Network Analysis AI

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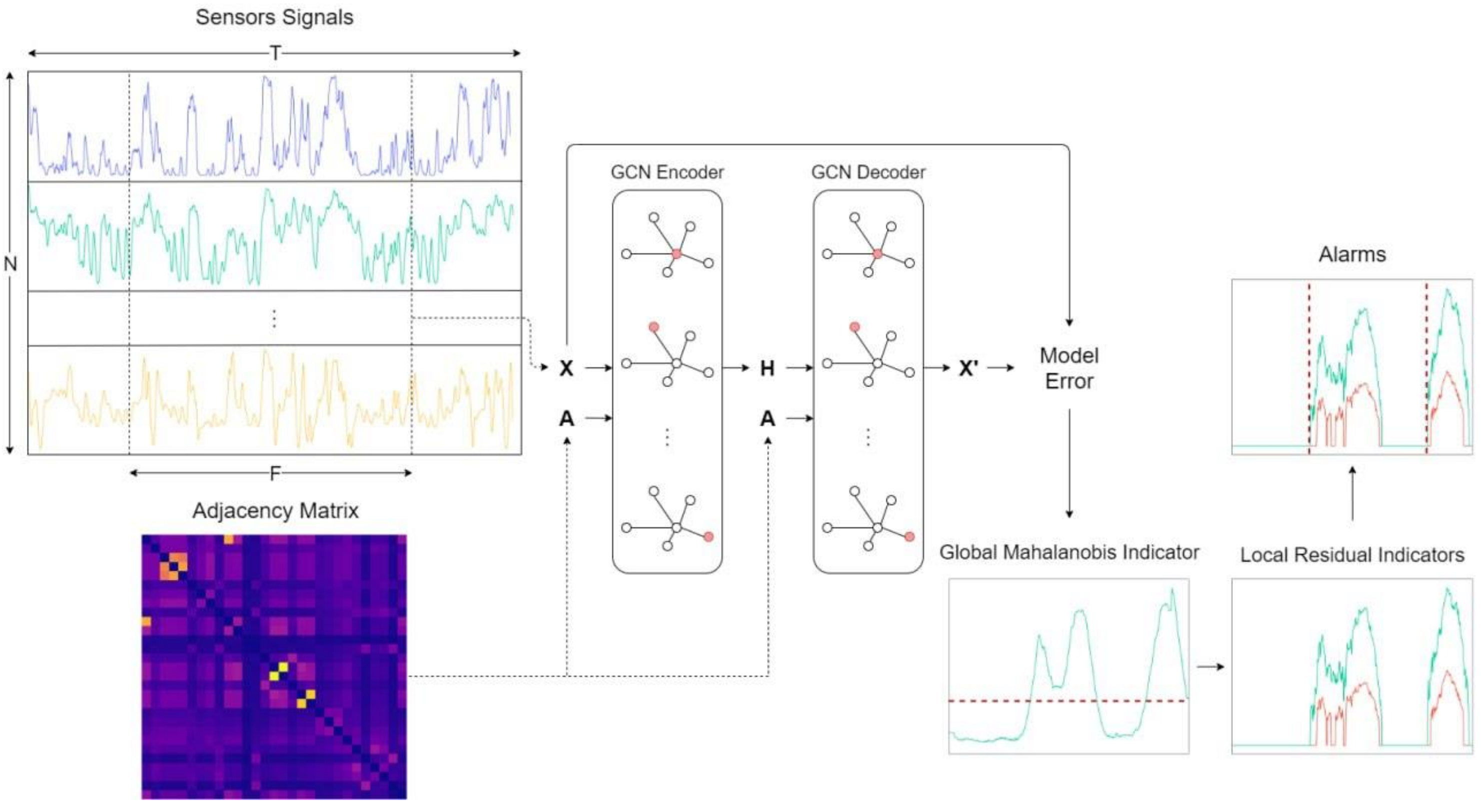
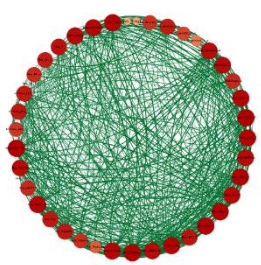
Predicting operations in Multi-MW HAWT

Sensor network mapping using AI





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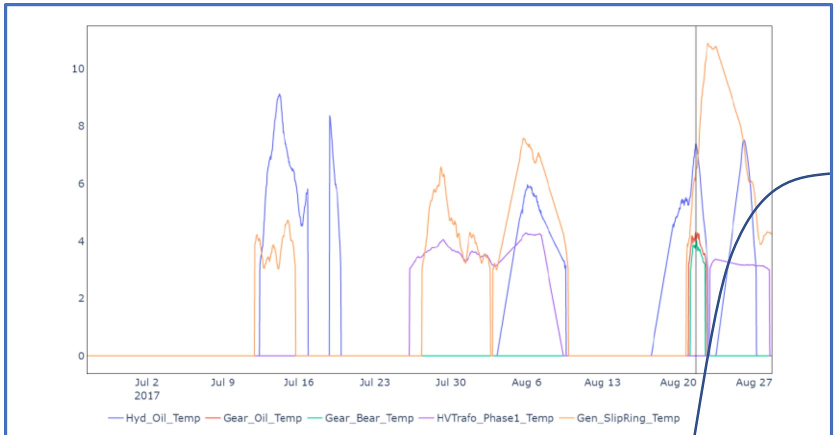
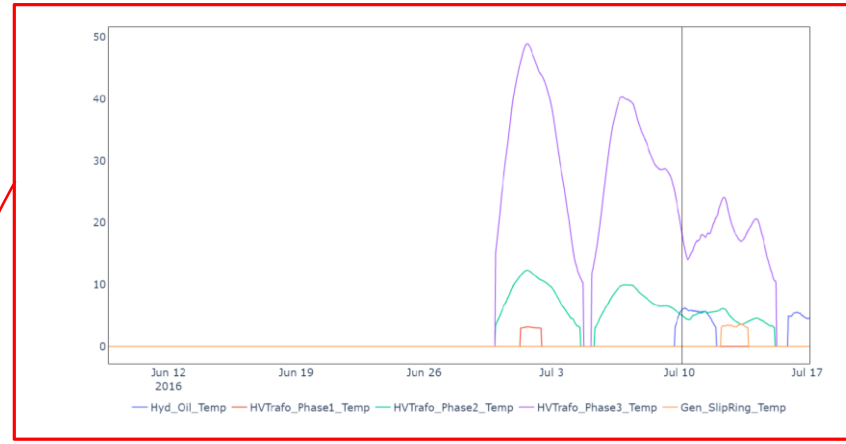
Predicting operations in Multi-MW HAWT

Predictive Maintenance in Wind Turbines

Plot of the model reconstruction errors of the turbine SN (vertical black line represents the failure occurrence time)





Component	Type of failure	Turbine ID
Gearbox	Pump damaged	T01
Generator	Generator Replacement	T06
	Generator Damaged	T07
	Electric circuit error	T11
Generator Bearings	High temperature	T07
	High temperature	T09
	Generator Replacement	T09
Transformer	Fan damaged	T01
	High temperature	T07
Hydraulic Group	Error in pitch regulation	T06
	Oil leakage in hub	T07
	Error in the brake circuit	T11

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Predicting operations in Multi-MW HAWT

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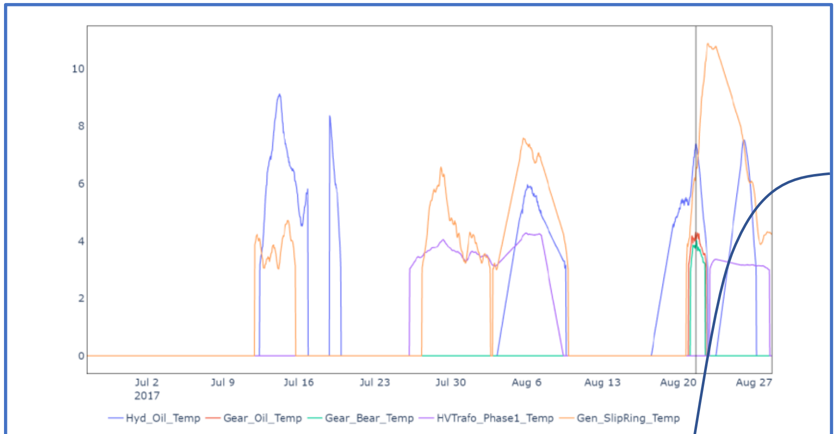

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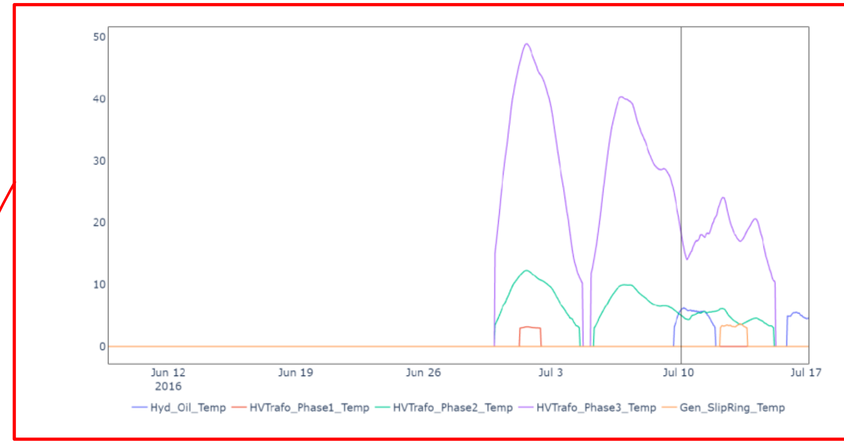

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	High temperature	T07
Hydraulic Group	Error in pitch regulation	T06
	Oil leakage in hub	T07
	Error in the brake circuit	T11

F (hh)	Avg Advance (dd, hh:mm:ss)	P (%)	R (%)	F1 (%)
1	4 days, 4:21:12	13	14	14
6	25 days, 21:53:34	55	79	65
12	26 days, 5:40:42	69	79	73
24	33 days, 11:53:51	81	93	87
36	32 days, 5:48:51	86	86	86
48	32 days, 1:47:25	92	86	89
58	29 days, 1:37:51	92	79	85
72	29 days, 8:37:51	79	79	79
84	32 days, 13:44:34	71	86	77

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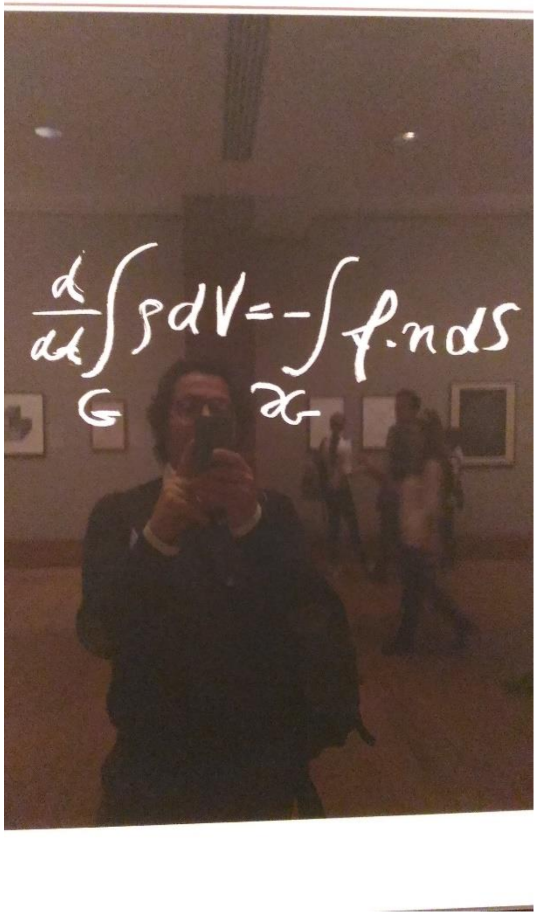
Conclusions

Industrial metrology is the enabling factor to disclose digital twin potentials and create so-called physical data servers

Sensor network perspective enables a *holistic view* of production systems meaning that all the relevant qualities are brought together to form a complete basis for evaluating process/product/operation quality

Grazie

Signals are not to provide numbers but insights



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