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Intelligence in Energy Management

Data Science & Big Data Analytics

Caso Studio di Modellizzazione di un Sistema di Manutenzione Predittiva per Turbine Eoliche

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Agenda

- **Background**: Wind Energy Overview
  The Importance of Predictive Maintenance
  State of the Art

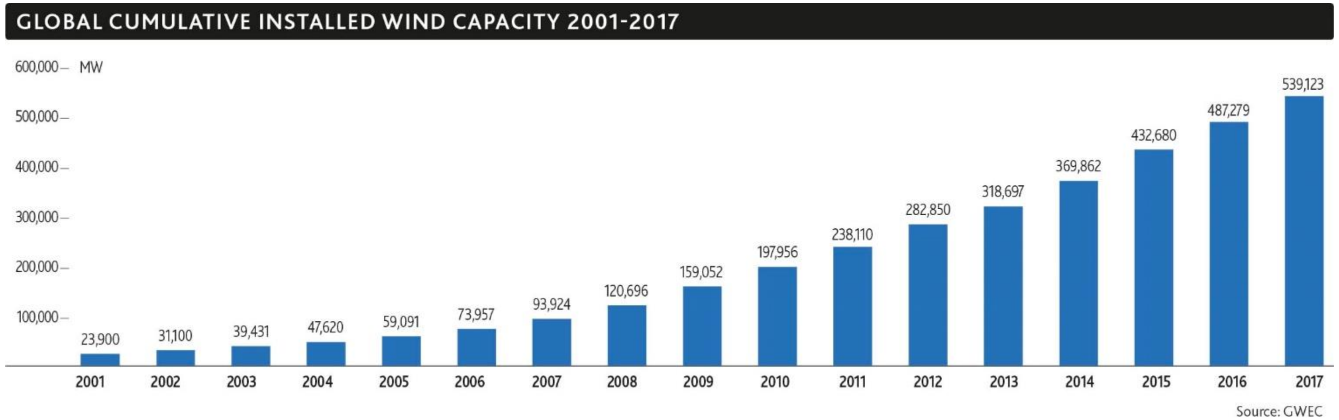
- **Model Requirements**: Definitions
  MATLAB Key Features for Predictive Model prototyping

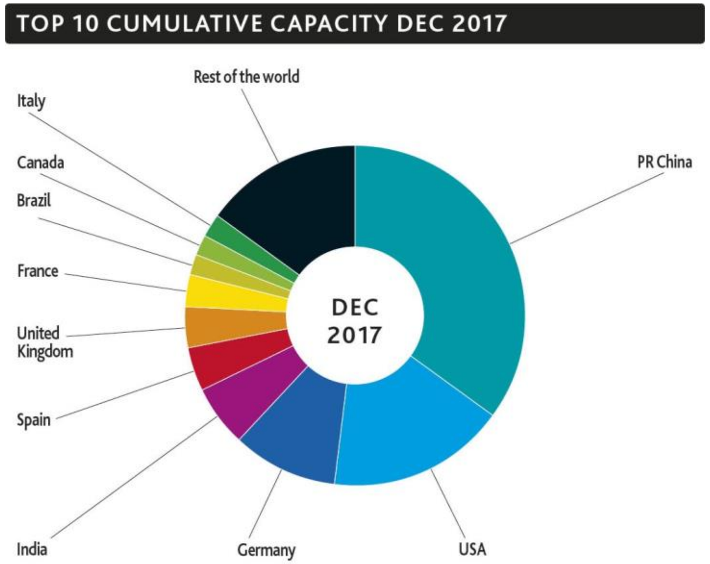
- **Model Development**: Model Architecture
  - Wind Turbine Components
  - Preprocessing
  - AANN + T^2
  - KPI Index and Anomaly Detection

- **Results**: Case studies
  Offline (Historical) Performances
  Online Performances
  Wind Farms Overview
  Data Analytics Dashboard

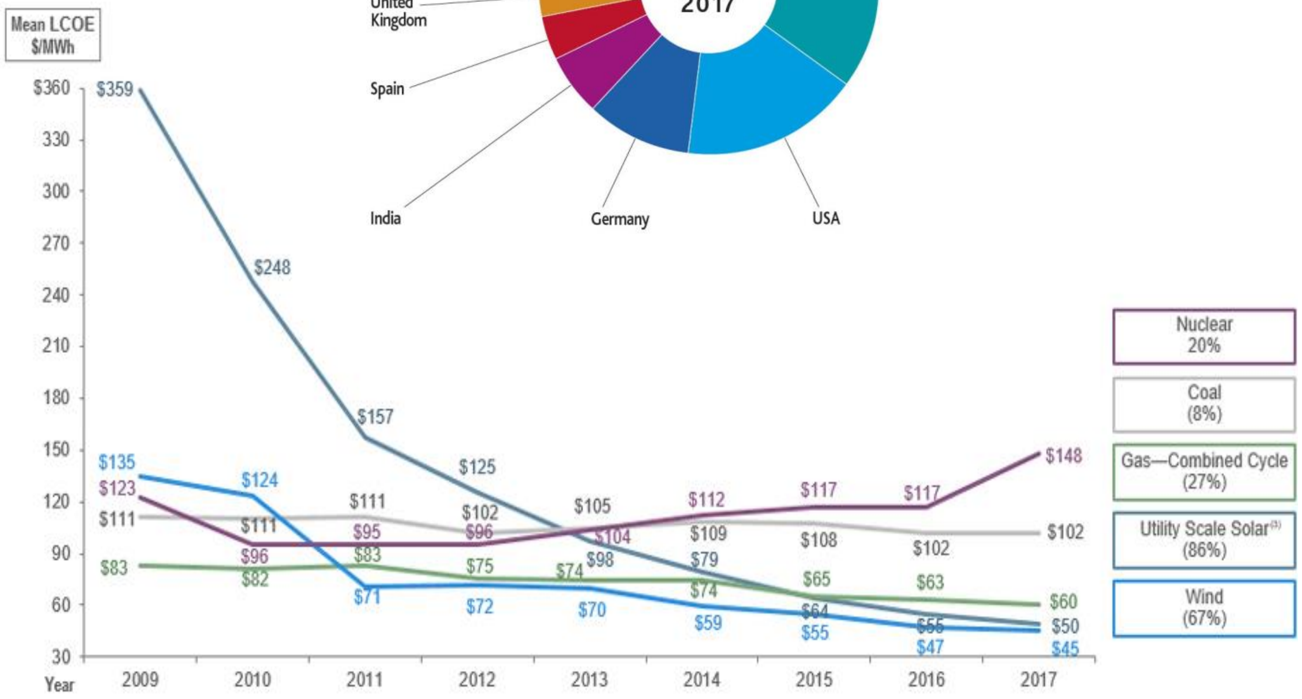
- **Conclusions and Forward Plan**

Background: Wind Energy Overview





- World Wind Energy capacity overcome **500 GW** in 2017
- Around **25%** share of World REN capacity
- **10%** growth last year
- The LCOE for WD decreased from almost 400 $/MWh in 1983 to almost **45 $/MWh** in 2017, a >**85%** decline
- O&M costs may represent up to **20-25%** of LCOE



Background: the importance of Predictive Maintenance

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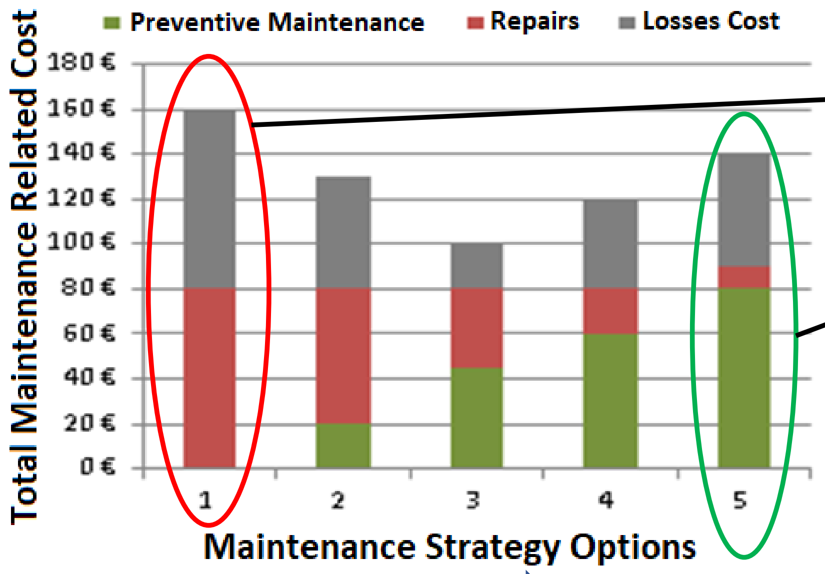
MAIN REASONS	The **growth** of WD power production at global level
	Remote locations of WD farms, making difficult their maintenance
	Management of unexpected failures has a significative impact on the total income from generation due to the **production loss**, **component replacement and service crew costs**
CONCEPTS	**Preventive Maintenance:** the definition of a strategy that can identify problems as soon as possible, in order to start maintenance activities, minimizing production loss



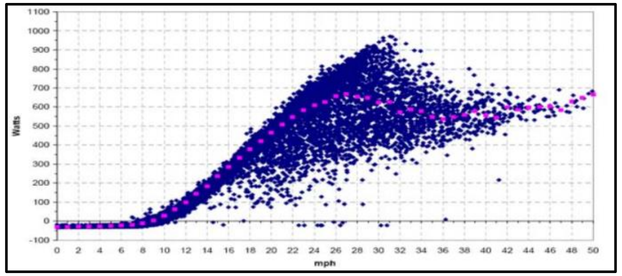
REACTIVE → **PREVENTIVE**

*The **more infrequent** is the Preventive Maintenance, the more **reactive** repairs will be performed, causing high cost due to plant downtime and significant losses*

*The **more accurate** is the Preventive Maintenance, the more losses will occur due to the plant downtime*

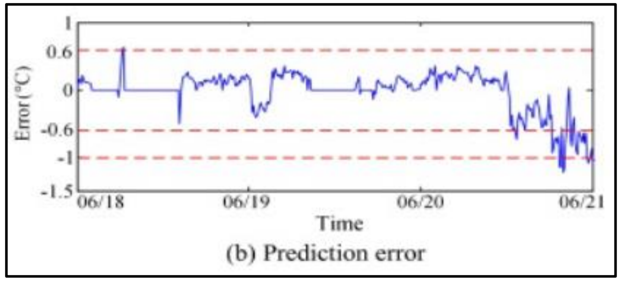
The optimum is located in the middle, i.e. making **Predictive Maintenance**: the definition of strategy that exploits signal collected from the plant **to predict optimum operation output and identify in advance possible failures**

Background: State of the Art



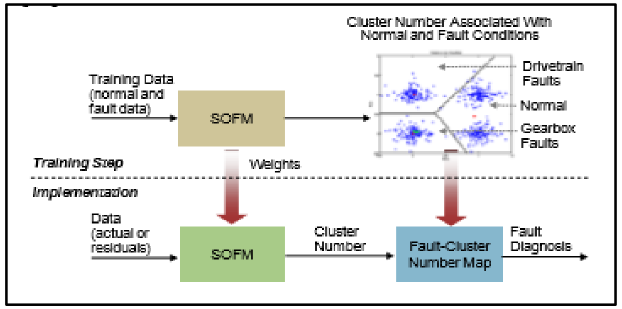
Power Curve Models

- ▼ It does not detect specific component fault: it treats the wind turbine as a whole



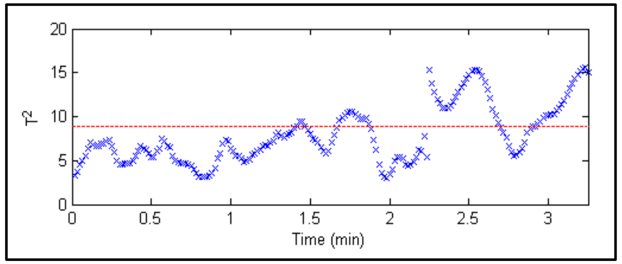
Condition Parameter Prediction Models (CPPM)

- ▲ It predicts specific component faults up to 4 weeks in advance
- ▼ The accuracy of the forecasting algorithm affects the sensitivity of the anomaly identification



Classification and Clustering Models

- ▼ Prediction time horizon is generally smaller than the one of CPPM (< 1 weeks)



Classic Statistical Models

- ▲ Prediction time horizon may be long as for CPPM
- ▼ T2 requires predictors normalization

Model requirements: Definitions

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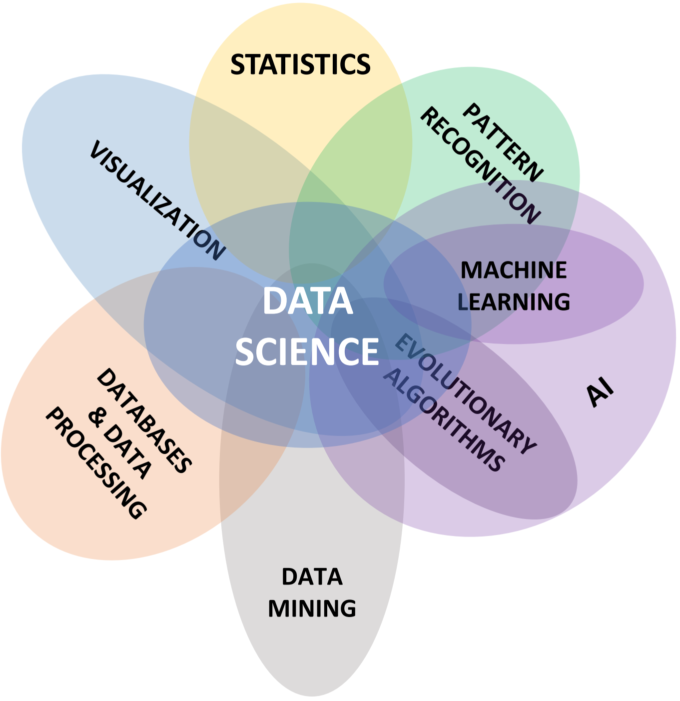
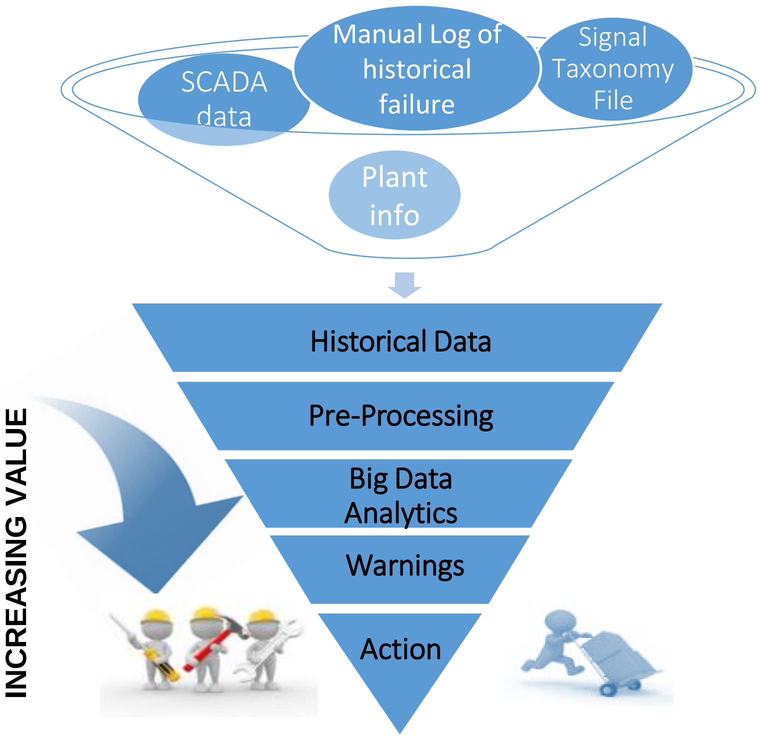
Objectives

Implementation of advanced predictive solution through Big Data technology application in order to monitor, detect and prevent **faults at Gearbox and Generator level** and reduce lost production for WD farms with different Wind Turbine Manufacturer

Multidisciplinary Approach



Big Data approach



Heterogeneus sources and data

Data of different types:

1. Related to energy conversion system (e.g. active power)
2. Component-specific (e.g. bearing temperature)
3. Historical alarms

Data from heterogeneous sources:

1. SCADA data (e.g. temperature, electrical signal, shaft speed)
2. Signal Taxonomy
3. Plant Information

Demanding Preprocessing

MATLAB Key Features for Predictive Model prototyping

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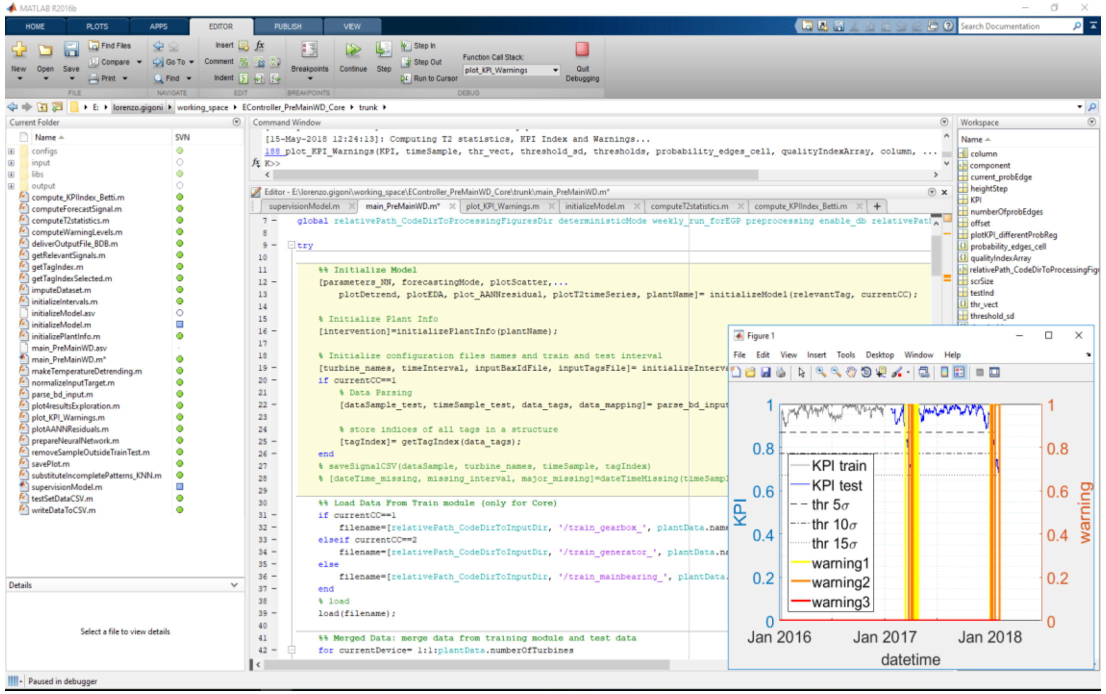
- ✓ Full set of Statistics and Machine Learning algorithms
- ✓ Easy import of data from relational database by means of the Database Toolbox and `readtable` command
- ✓ Easy manipulation of heterogeneous data through the use of table, cell array and structure types
- ✓ Easy manipulation of timestamp data including timezone (`datetime`)
- ✓ Easy development of Model prototype



- ✓ High speed processing on large datasets both on cluster and cloud by means of Parallel computing Toolbox
- ✓ Easy deployment either as standalone applications or as mapreduce programs to Hadoop clusters
- ✓ An open exchange of material for the Matlab user community (Matlab File Exchange)

Model development: Model Architecture–WT components

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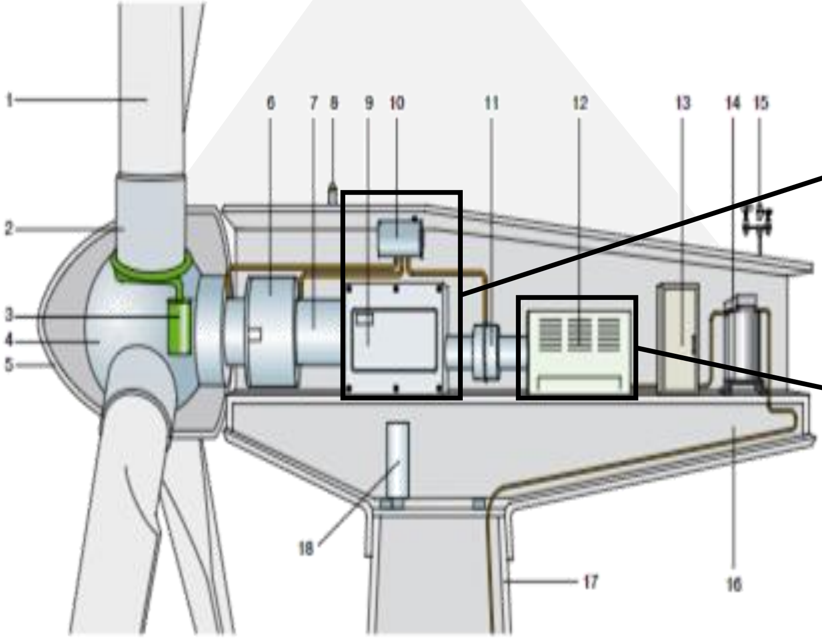
MAIN COMPONENT SELECTION RULES

- ***Most critical*** *component:*
  - *cost of component*
  - *cost of the intervention*
- ***State of the Art*** *of SCADA data anomaly detection model*
- *Case Studies Availability*
- ***Signal Availability***



Gearbox

- Energy Conversion System Parameters
- Gearbox specific signals

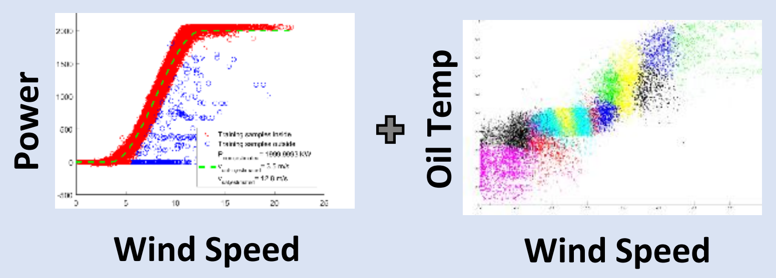
Generator

- Energy Conversion System Parameters
- Generator Specific Signal

- ✓ **26 billion of SCADA Data** used as training per each Wind Farm
- ✓ **1.5 billion of SCADA Data** processed each week
- ✓ Data archived and preliminary preprocessed with the Big Data infrastructure **Microsoft Azure Data Lake Analytics**

Model development: Model Architecture - Preprocessing

Wind Turbine Generator Data → **Preprocess Raw Data** → AANN + T^2 → KPI Index evaluation → ANOMALY DETECTION



Bivariate Outlier Removal:
power curve fitting

- Constrained optimization of the cubic curve coefficients
- Threshold band based removal

Multivariate Removal[1]:
K-Means clustering based method

- A multivariate outliers removal is more consistent with *Hotteling T^2*, which is a multivariate quality control chart

1) Monitoring Wind Farms With Performances Curves, Andrew Kusiak, IEE Transactions of Renewable Energy, 2013.

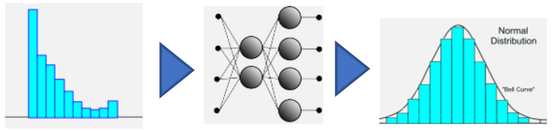
Model development: Model Architecture - AANN + T^2

Wind Turbine Generator Data → Preprocess Raw Data → AANN + T2 → KPI Index evaluation → ANOMALY DETECTION

MACHINE LEARNING[1]

Auto Associative Neural Network

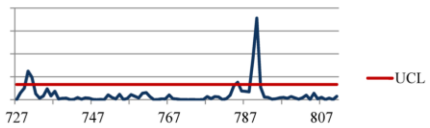
Multivariate Distribution **AANN** **Normalized Residual**



- Data signals are trasformed to be approximately normally distributed

CLASSIC STATISTIC APPROACH[2]

T^2 Hotteling Control Chart



- A statistical process control based on a multivariate analysis is used to monitor and control the variables affecting the system under investigation

1) *Integrating Auto-Associative Neural Networks with Hotteling T2 Control Charts for Wind Turbine Fault Detection, H.Yang, Energies, 2015.*
2) *The application of Hotelling's T2 control chart in an automotive stamped parts manufacturing plant, Muzalwana Abdul Talib et al (umexpert-um.edu).*

Model development: Model Architecture – KPI & Anomaly

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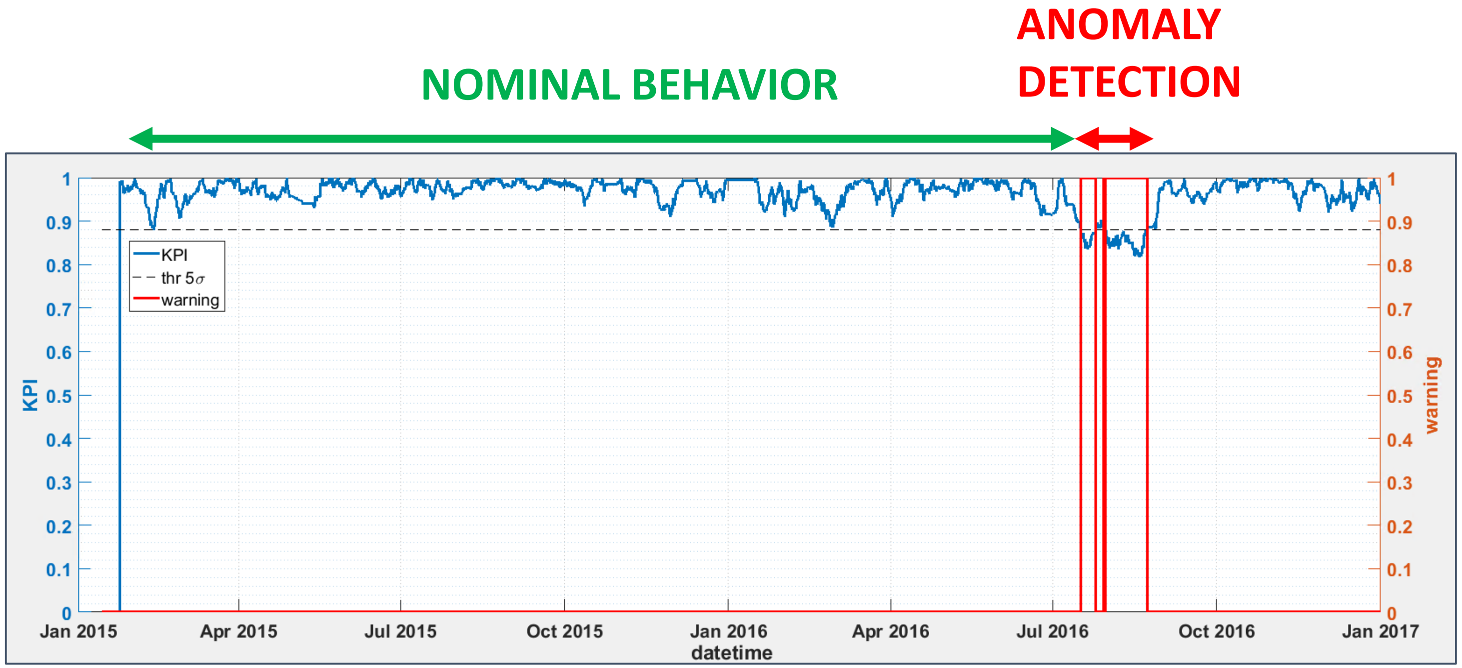
Wind Turbine Generator Data → Preprocess Raw Data → AANN + T2 → KPI Index evaluation → ANOMALY DETECTION

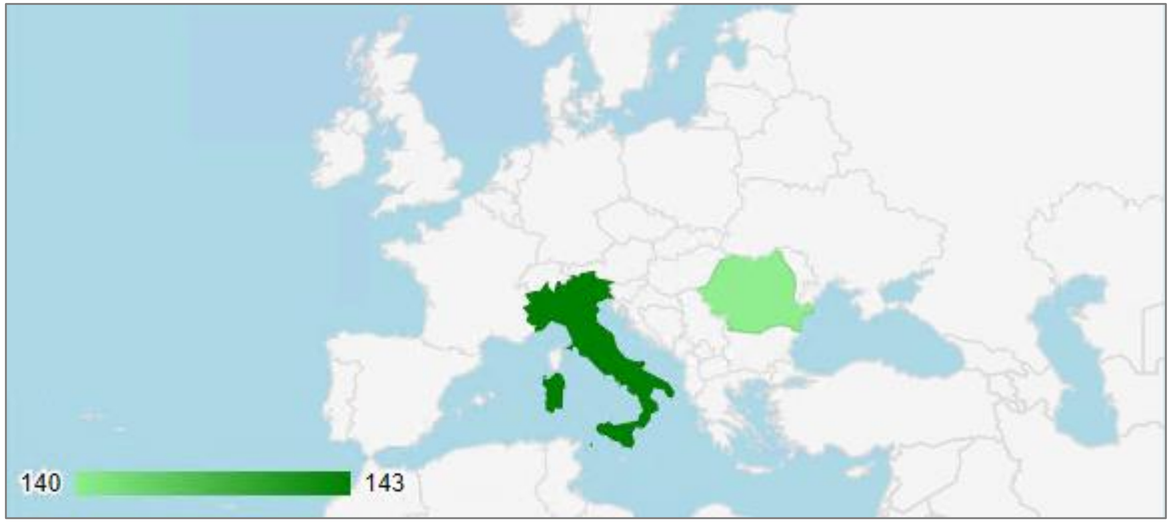
- The *i-EM* proprietary KPI Formula monitors population housing in different T^2 sub-regions
- The last 7 days of the WTG operative conditions are supervised
- Model parameters are tuned accordingly to offline WTG analysis



Results: Case studies

Wind Farm statistics:

- ✓ **Total Nominal Power Plant**: > 280 MW
- ✓ **Maximum Nominal Power Plant**: 70 MW
- ✓ **Total number of wind turbines**: 150
- ✓ **Maximum number of wind turbines for plant**: 35
- ✓ **Number of manufactures**: 3
- ✓ **Country:** Europe
- ✓ **Total Plants tested**: 6



Wind Farm	Country	No. Wind Turbines	Turbine Power (MW)	Turbine Manufacturer
#1	ITALY	34	1.50	A
#2	ITALY	9	2.00	B
#3	ITALY	9	2.00	B
#4	ITALY	28	2.00	B
#5	ROM	35	2.00	C
#6	ROM	35	2.00	D

- ✓ **Historical optimization period:** 2014-2016
- ✓ **Online test period:** 2017

Results: Offline (Historical) Performances

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WF1 WT26 Manufacturer A

- Component: *generator bearing fault*
- Detection w/o Predictive Service: *26th June 2016*
- Outage duration: *36 days* *(up to 1st August)*

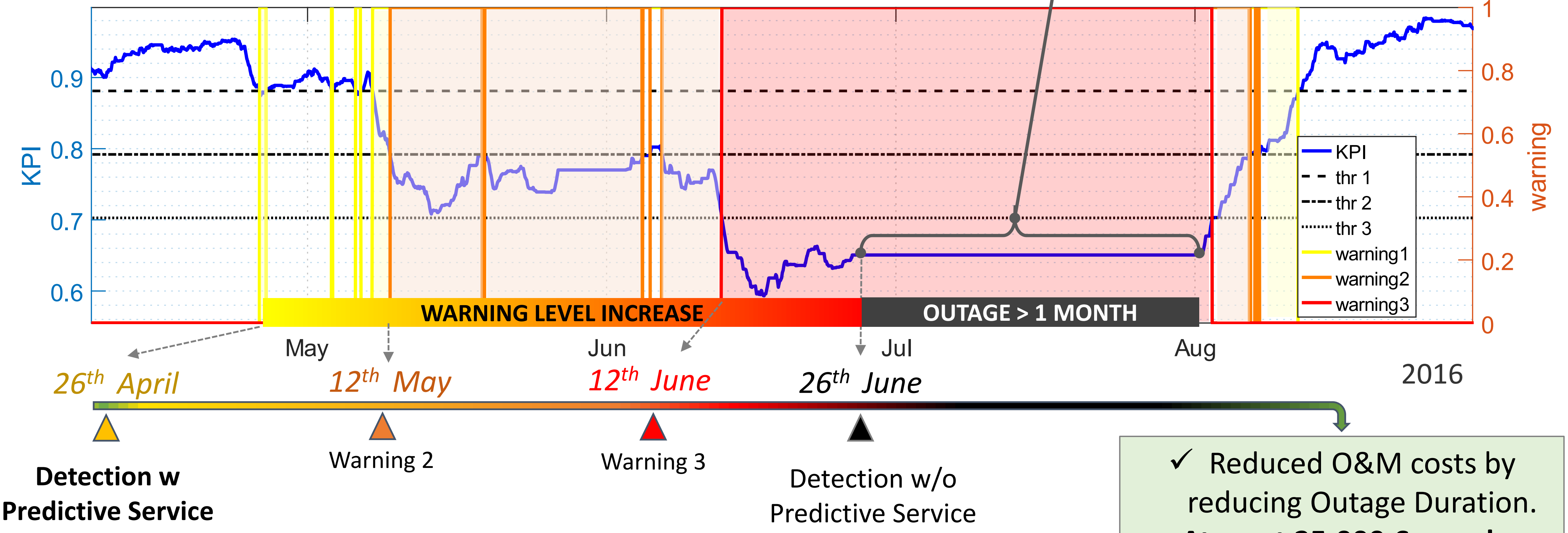
OUTAGE > 1 MONTH

W/O PREDICTIVE SERVICE

Lost Production ≈ *504 MWh*

Lost Revenue ≈ *25.000 €*

W PREDICTIVE SERVICE



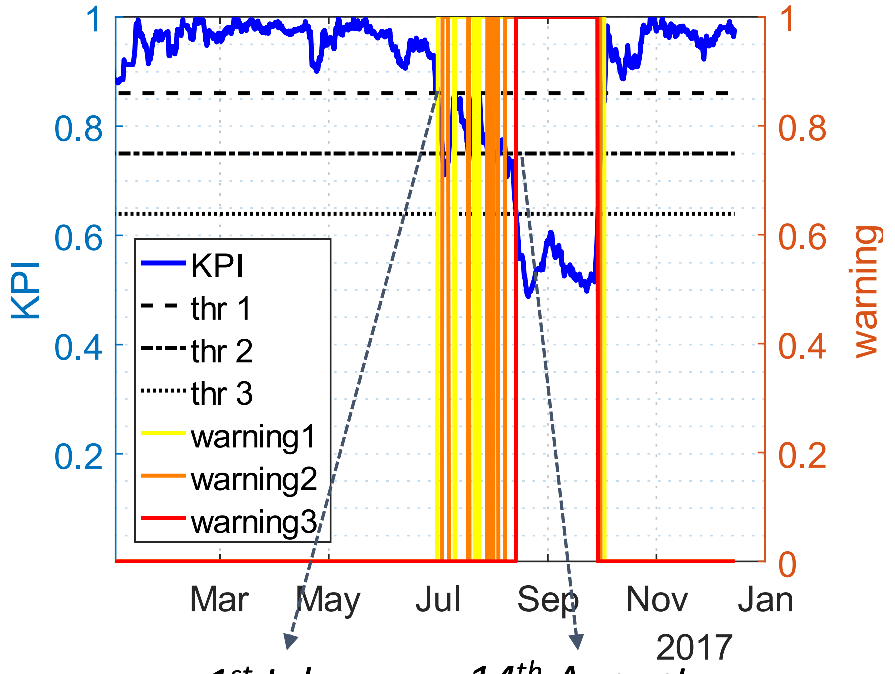
✓ Reduced O&M costs by reducing Outage Duration. **At most 25.000 € saved.**

Results: Online Performances

WF5 WT19 Manufacturer C

- Component: *gearbox cooling system*
- Detection w Predictive Service*: July 2017*
- Outage duration: *< 1 days*

✓ KPI degradation corresponds to the bearing temperature increase

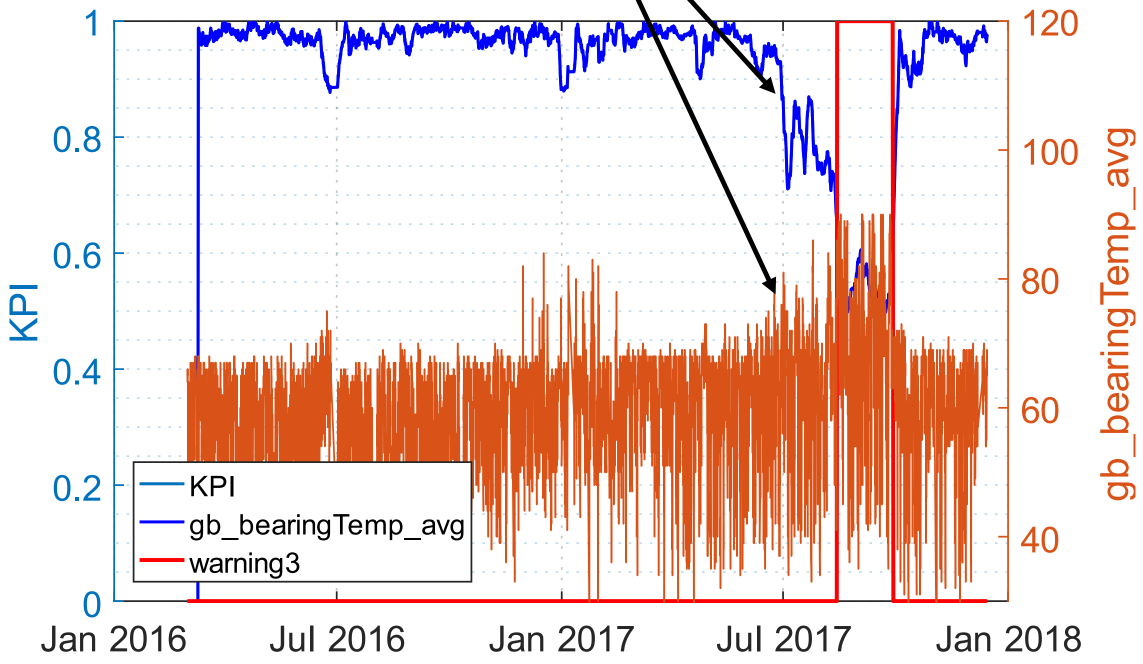


1st July

WARNING 1

14th August

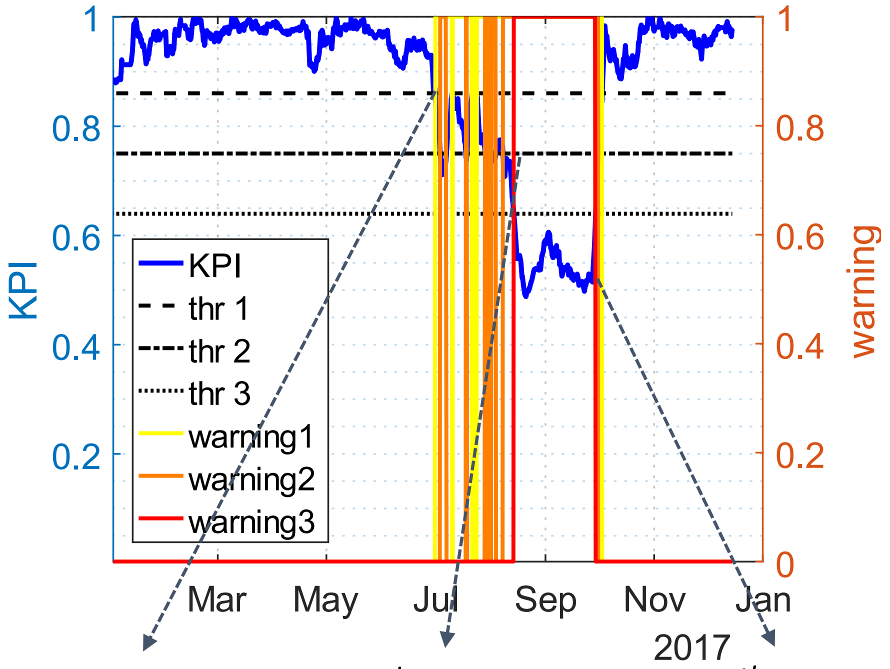
WARNING 3



Results: Online Performances

WF5 WT19 Manufacturer C

- Component: *gearbox cooling system*
- Detection w Predictive Service*: July 2017*
- Outage duration: *< 1 days*



1st July — WARNING 1

14th August — WARNING 3

27th Sept — MAINTENANCE

PREDICTIVE MAINTENANCE STRATEGY

1st July

Supervision Model Warning delivery to Wind Farm operators

1st July – before 27th September

Diagnosis of cooling system issue

Maintenance Scheduling

27th September

Intervention

i-EM Service

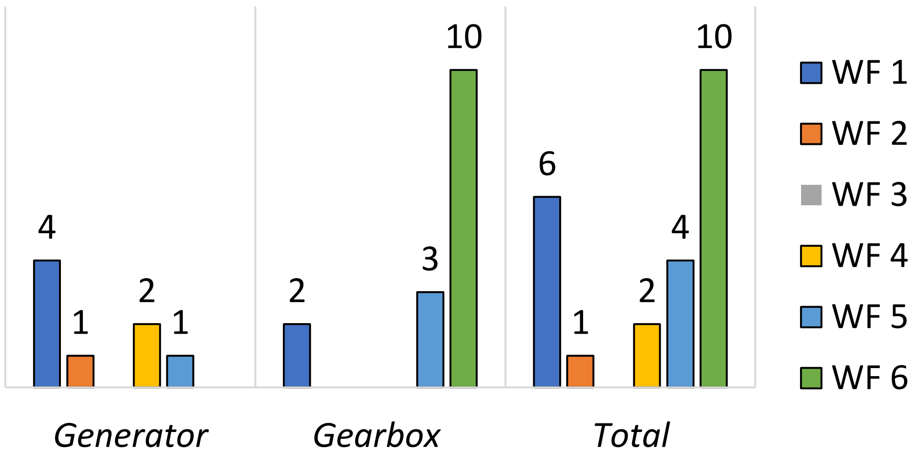
- ✓ **Early detection/ prediction of issue**
- ✓ **Reduce downtime**
- ✓ **Mitigate O&M costs/ LCOE reduction**

Results: Wind Farms Overview

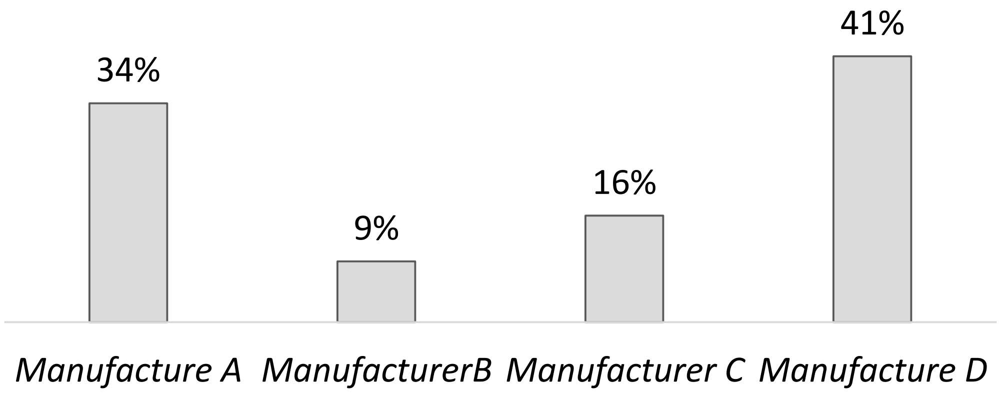
Warnings Overview

Wind Farm	Turbine Power (MW)	Turbine Manufacturer	Anomalous Cases Detected (year 2017)
#1	1.50	Manufacturer A	***6 cases delivered*** *(2 Gearbox, 4 Generator)*
#2	2.00	Manufacturer B	***1 case delivered*** *(Generator)*
#3	2.00	Manufacturer B	No cases delivered
#4	2.00	Manufacturer B	***2 cases delivered*** *(2 Generator)*
#5	2.00	Manufacturer C	***4 cases delivered*** *(3 Gearbox, 1 Generator)*
#6	2.00	Manufacturer D	***10 cases delivered*** *(10 Gearbox)*

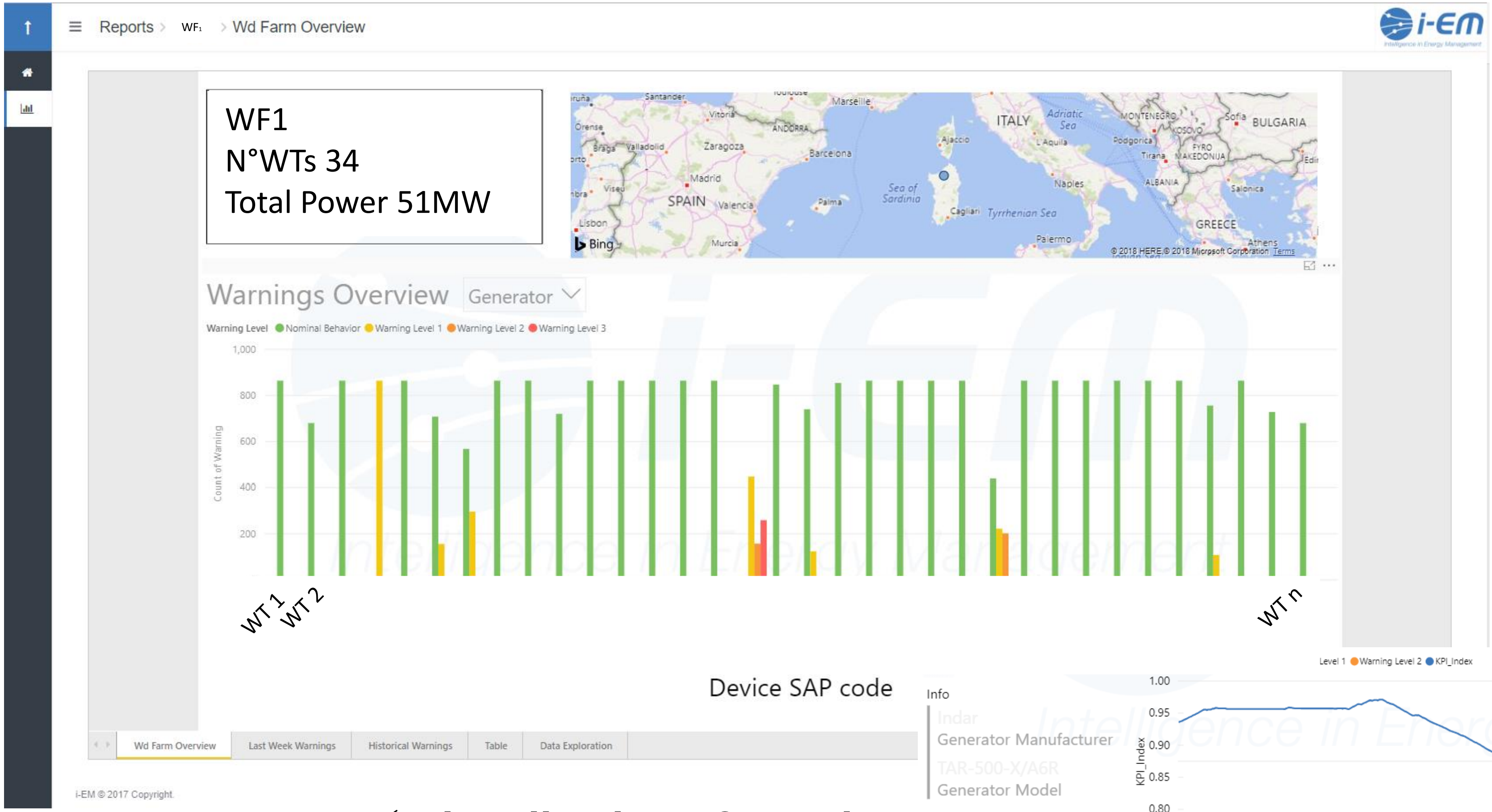
Wind Farms Warnings Statistics

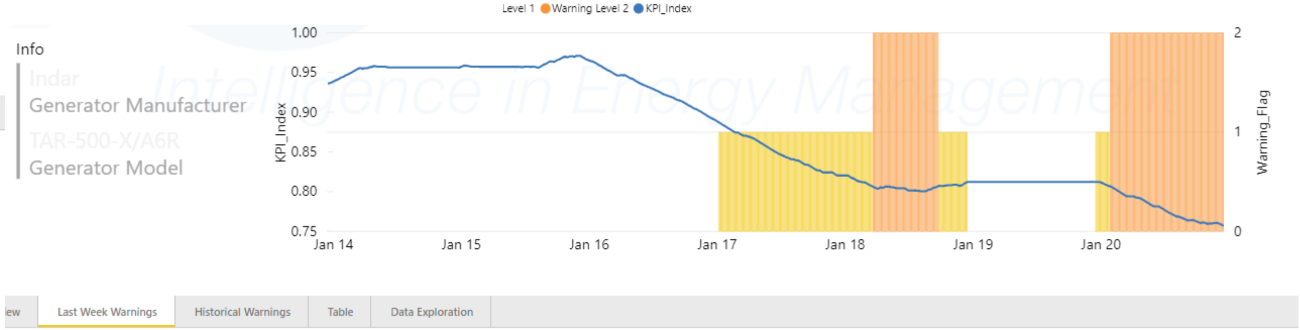


Manufacturer Statistics: Normalized Number of Warnings



Results: Dashboard





✓ ***easy visualization of critical conditions***

✓ ***visualization of warning time-evolution***

Conclusions

- Nowadays Predictive Maintenance represents a key strategy for maximizing wind farm production
- A Combination of Machine Learning (ML) and classical statistical algorithms within a multivariate approach has been implemented to predict fault events at different Wind Turbine components, with a lead time up to 1 month w.r.t. fault occurrences
- The Model has been tested exploiting a large amount of data from different spatial, temporal and technological points of view
- The fast service deployment on new wind farms allows a rapid extension to unknown plants and technologies
- Use of MATLAB has allowed to successfully:
  - ✓ Import and handle heterogeneous data from different sources
  - ✓ Implement and compare quickly different ML algorithms
  - ✓ Parallelize the model with minimum effort
  - ✓ Develop quickly the Model prototype
  - ✓ Deploy the application to the final platform

Thank you!

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