Where Industry meets Data Science

Using data for specific purposes within the Offshore wind industry

DIGITALIZATION & DATA ANALYTICS

22GW

We manage over 22GW of real-time operational data from solar PV, wind and storage assets

>7.9TWh

Our data-driven energy efficiency implementation services have saved over 7.9TWh over the last 3 years

>12500

Our analysts review over 12,500 wind, solar and grid sensors each week

>99%

DNV GL's Smart Cable Guard detects the location of electrical cable network failures with an accuracy of greater than 99% and can prevent 65% of such failures

WIND

65GW

We have analysed over 65GW of operational wind projects

2400+

We conduct over 2,400 wind inspections each year

1GW

We are technical advisor to the lenders on Fosen, the world's largest onshore wind farm at 1GW

90%

90% of certified offshore wind farm projects utilized our project certification

No. 1

Our BLADED tool is the world's best-selling design tool for wind turbines

1st

We conducted the world's first hardware-in-the-loop testing for an entire wind farm

*Our testing, certification and advisory services are independent from each other

Wind operations today

- Goals:
  – Increase turbine performance
  – Reduce downtime
  – Decrease maintenance costs
  – Extend the life of assets beyond their original design

- Challenges:
  – Constant pressure to reduce costs and increase revenue
  – Strong focus on ROI means that it is difficult to dedicate resources to research and analysis

- Opportunities:
  – Increasing know-how as the industry matures
  – Proliferation of data that could be used to optimise operations

Data is becoming the new raw material of business

To drive down cost and keep the safety/security and quality at an acceptable level, the use of data is a key enabler

Why data management is needed

The primary driver for Data Management is to enable organizations to get value from their data assets, just as effective management of financial and physical assets enables organizations to get value from those assets.

- (Ref DAMA DMBOK 2.0)


Harvard Business Review

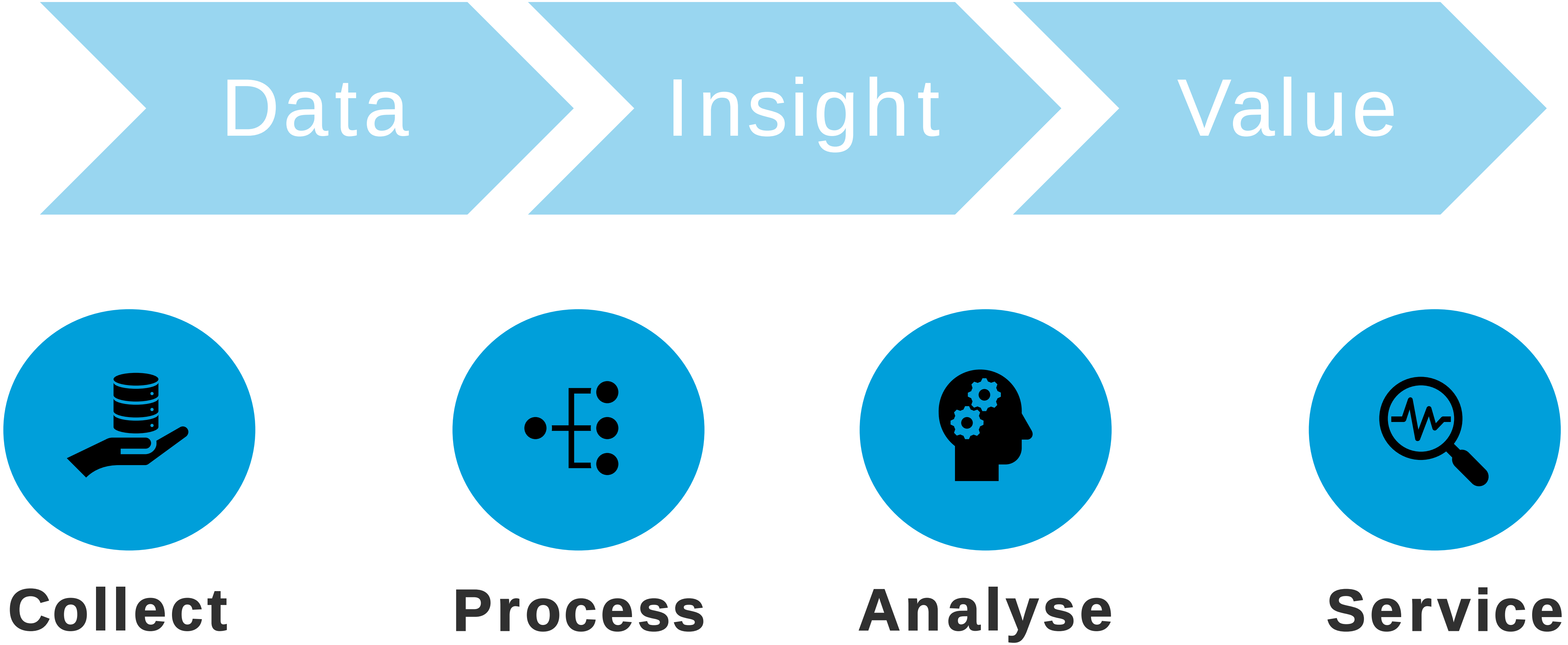
DATA

Bad Data Costs the U.S. $3 Trillion Per Year

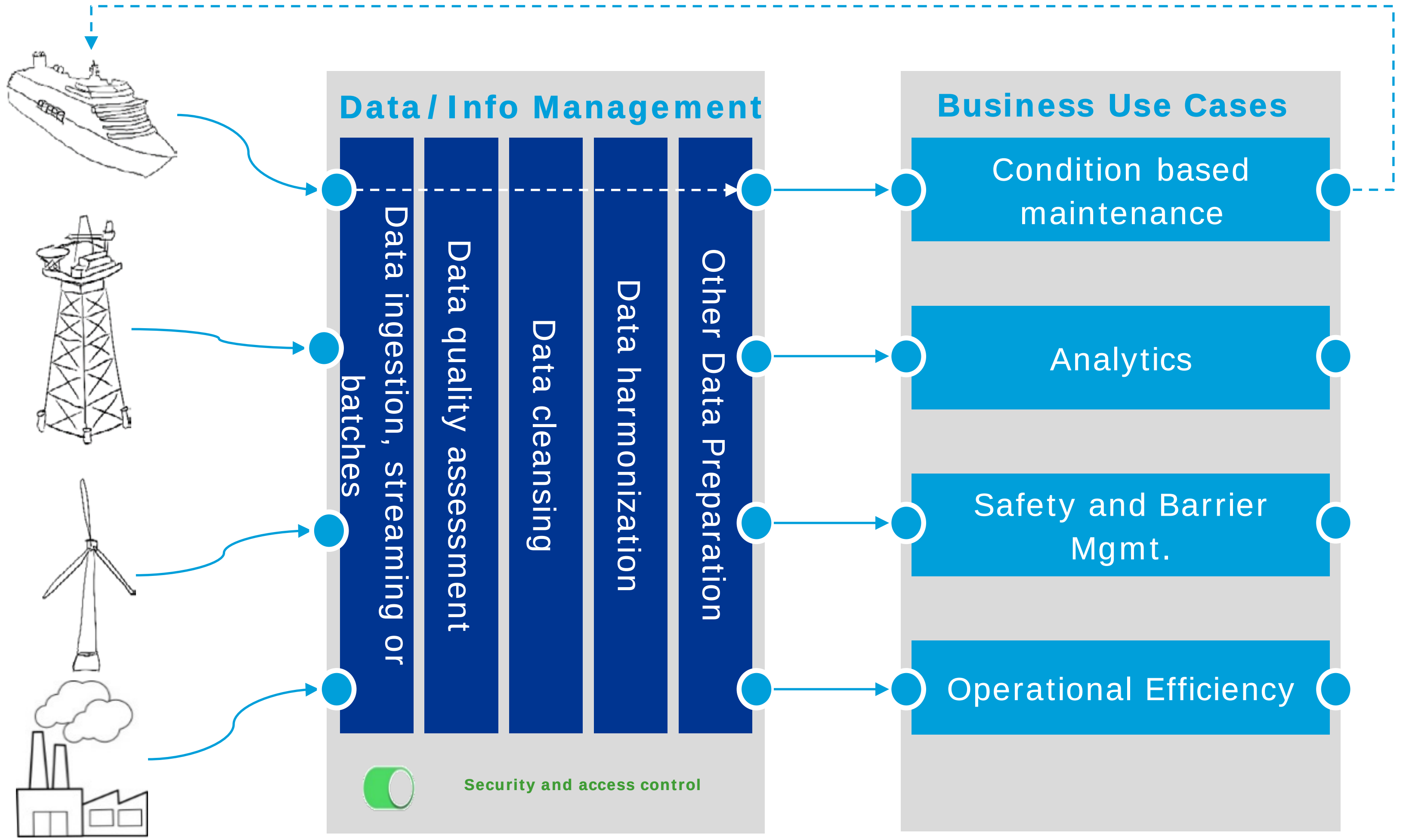
by Thomas C. Redman

SEPTEMBER 22, 2016

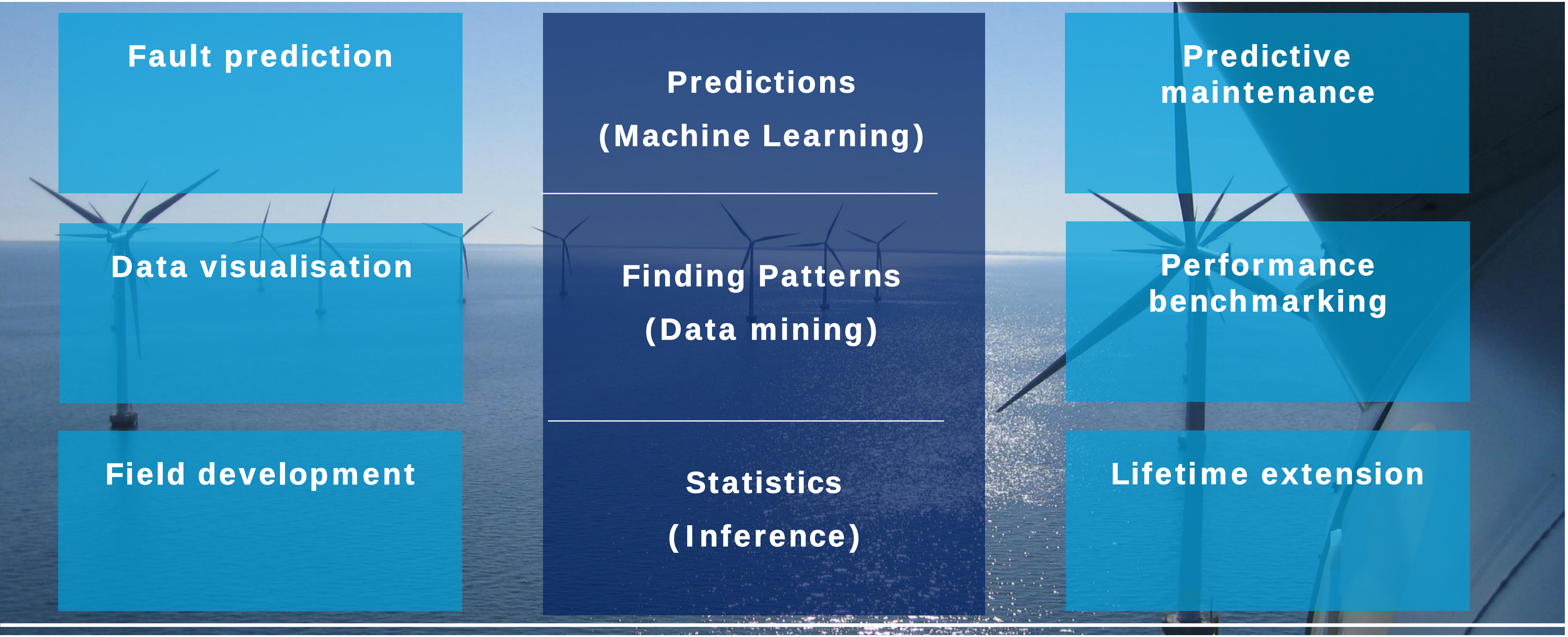
Getting value out of data - Conceptual Model



Creating value from data



Business use cases in the Offshore wind industry…



Fault prediction

Data visualisation

Field development

Predictions

(Machine Learning)

Finding Patterns

(Data mining)

Statistics

(Inference)

Predictive maintenance

Performance benchmarking

Lifetime extension

The value chain of data

Assets	Data Sources	Data types	Transfer methods	Data Integration, storage & processing

Data Sources

- HSEQ systems
- Maintenance systems
- Historians
- Control systems
- Monitoring systems
- External sources
- Etc.

Data types

Internal sources;

- Operational data
- Maintenance data
- HSEQ data
- Event data
- Sensor data
- Etc.

External sources;

- Weather data
- Grid data
- Satellite sensor data
- Etc.

Transfer methods

- Batch transfers
- Streaming

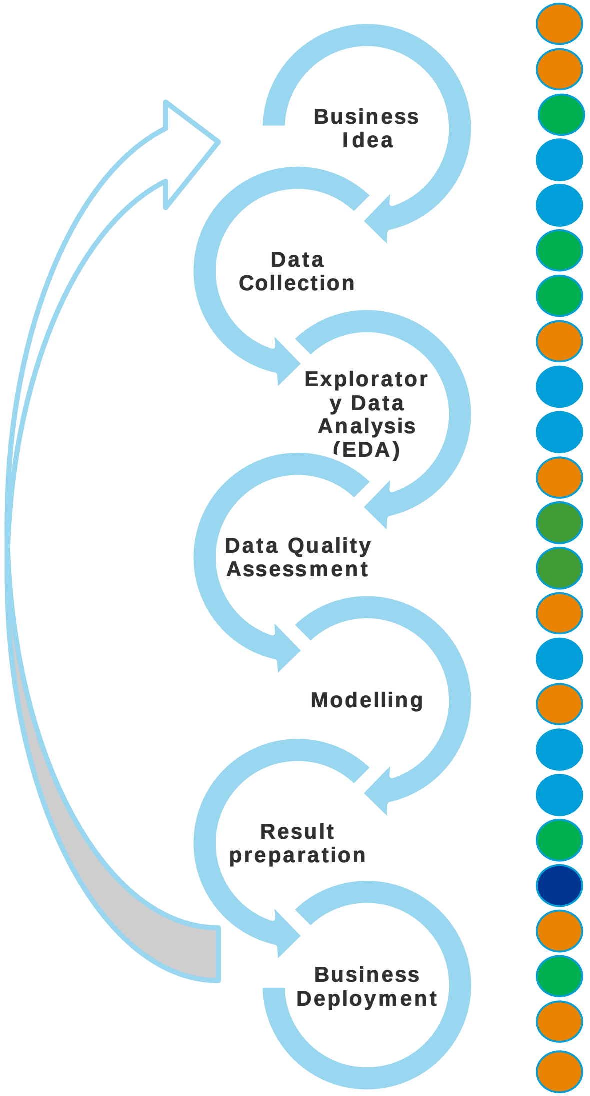
Data Integration, storage & processing

- Data Aquisition Services
- Data Ingest & contextualisation
- Data quality services
- Data analysis & modelling services
- Visualisation, reporting and sharing
- Data curation services

Data Storage – e.g. DNV GL Veracity

Deployment of models to 'edge'

The process of dealing with data – skills needed



Required skills

Business Strategy	Data Science
Data Engineering	Front-End Development

Considerations

- Do you have the relevant data?
- Are they available/accessible?
- Are they within acceptable ranges? Right quality?
- Can you build a model?
- Are you able to validate the model?
- Can the model be scaled, if applicable?
- Is the cost of storage and computation within target budget?

Barriers in process of dealing with data

Platforms, integrations, sharing ++

Contextualize, data quality, twins ++

AI / ML

From corporate entertainment to actual business impact

The “digital promise”: efficiency, autonomous operations, automation ++

Data made available → Data made usable → Data used for predictions →  → Predictions used for operational decisions

⚠ governance

sharing

⚠ data management

data quality

⚠ trust in ML

Trust in Data Quality

Data Quality

SYNTACTIC QUALITY

The degree to which data conform with the specified syntax; i.e., the requirements stated by the metadata.

Metadata can be legal values, data types and referential integrity, such as links between data parts, business vocabulary, and any defined business rules.

SEMANTIC QUALITY

The degree to which data correspond to what they represent.

For example, when a sensor measures 72 °C, the actual temperature should also be 72 °C at the point of measurement; if this is not the case, there is some amount of semantic error.

PRAGMATIC QUALITY

The degree to which data are suitable and useful for a particular purpose.

For example, if sensor measurements are needed every second, but they are received on average once per minute, then the requirement is not met and the data are considered to be of low pragmatic quality.

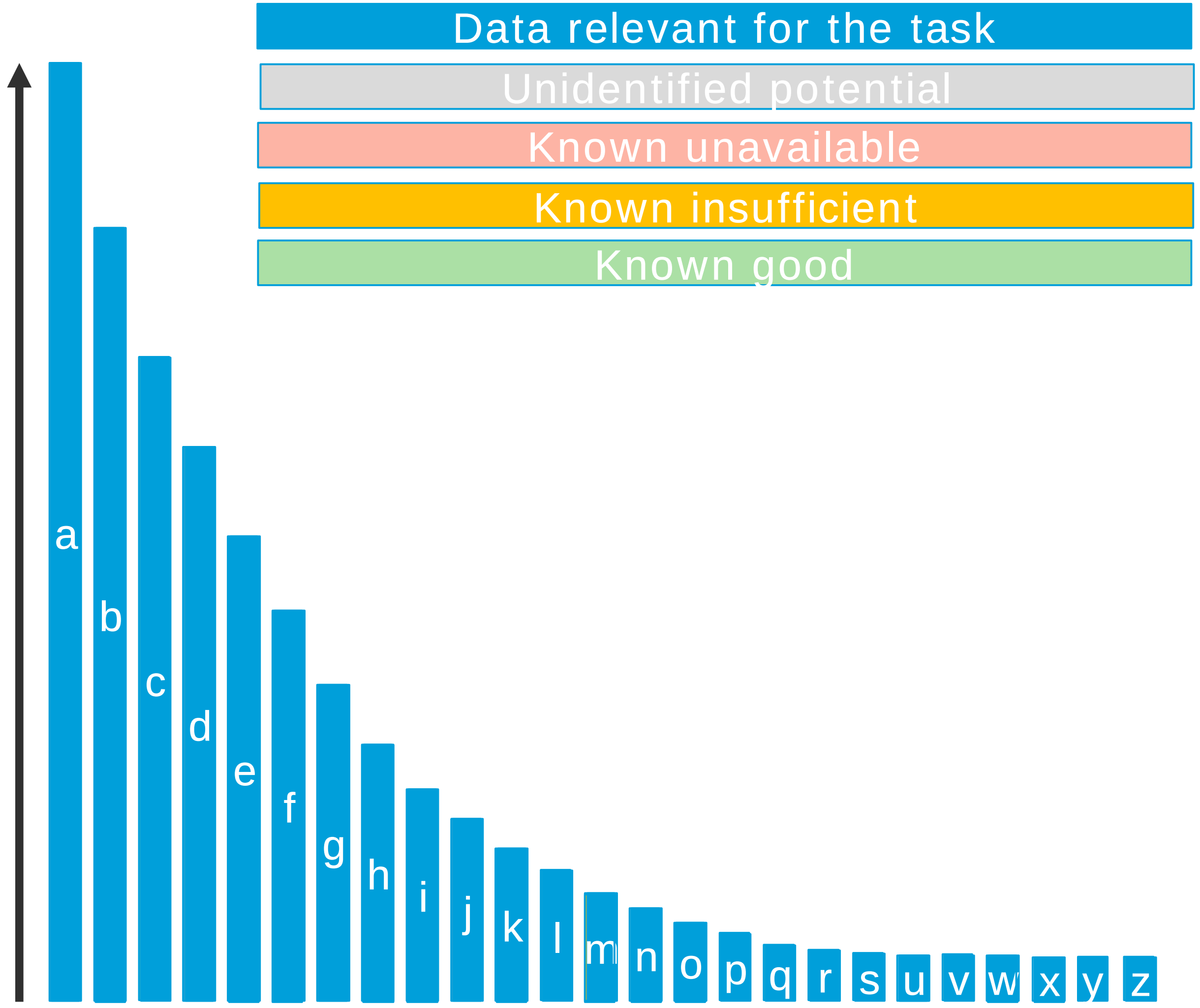
Importance of data to use case

	CM Measure tech A	CM Measure tech B	Failure modeling tech C	Failure modeling tech D	Failure modeling tech E	Condition test F	Condition test G
Parameter 1	1	1	1	1	7	9	0
Parameter 2	9	1	1	1	7	9	9
Parameter 3	9	5	5	7	7	1	1
Parameter 4	5	1	1	1	1	1	9
Parameter 5	0	1	9	1	1	1	0
Parameter 6	0	8	1	9	1	1	0
Parameter 7	8	0	9	0	0	0	5

0 = Data quality level low, 9 = Data quality level high

Data we have versus data we need to execute a task

Importance of contribution



$Y(t) = at+bt+ct+dt+et+ft+gt+ht+it+jt+kt+lt+mt+nt+ot+pt+qt+rt+st+ut+vt+wt+xt+yt+zt$

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Recommended practice RP-0497

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RECOMMENDED PRACTICE

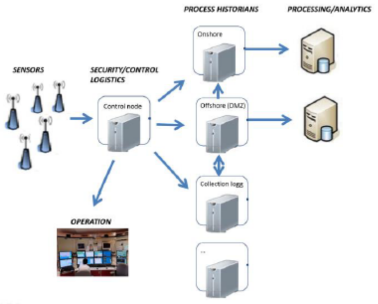
DNVGL-RP-0497 Edition January 2017

Data quality assessment framework

DNV·GL

Data Quality Assessment for Sensor Systems and Time-Series Data

Report No.: 2017-0058, Rev. 1.01
Document No.:
Date: 2017-02-09



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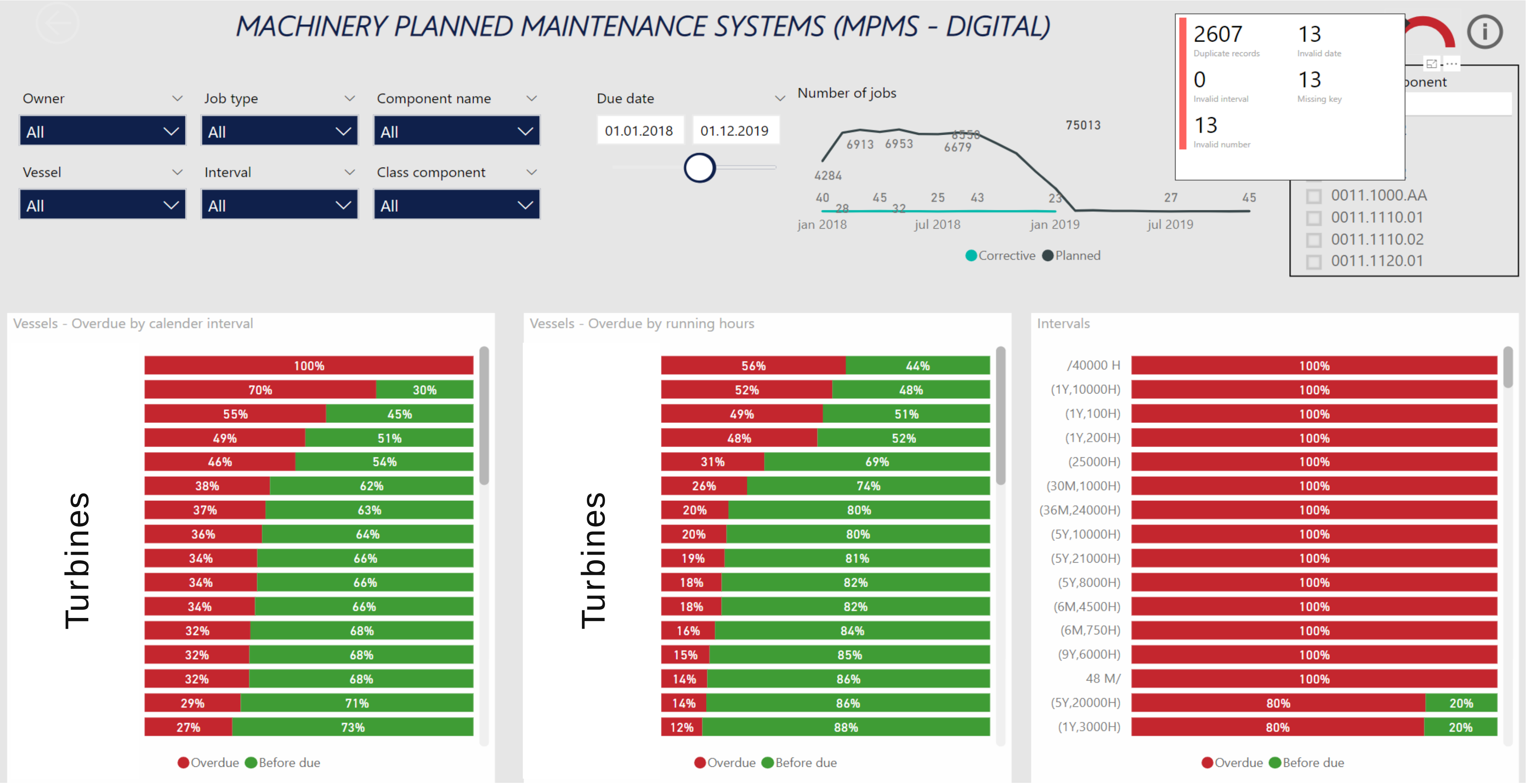
Maintenance example



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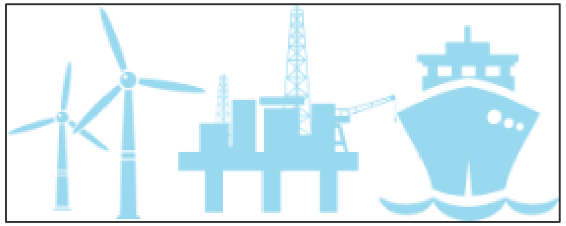
Ensuring data are fit for use

IoT

Sensor

Health data

Finance data



Record and store data (Data Asset) → Data Quality → Data fit for use → Model / Algorithm → Result / Prediction → Make decision

Trust

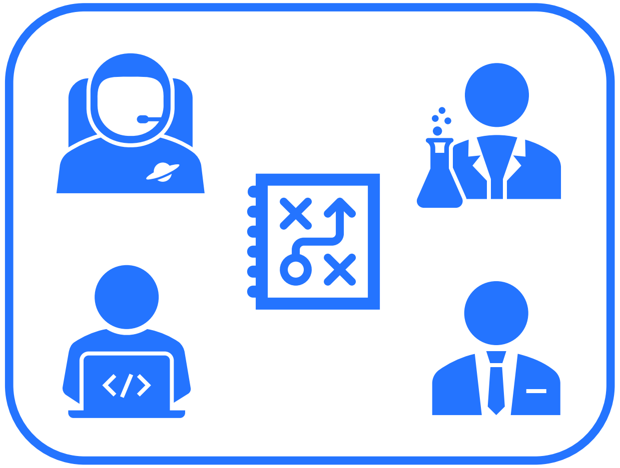
What is trust?

to believe that someone is good and honest and will not harm you, or that something is safe and reliable

source: Cambridge Dictionary

Who needs trust in Machine Learning

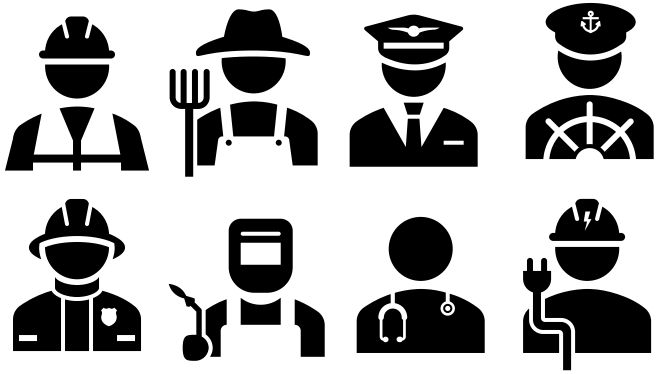
HONEST PREDICTORS AS



"you can trust us!"

the company

doing the ML



the users

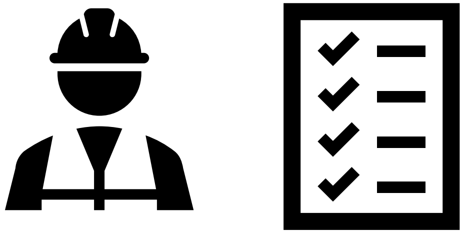
Quick'N'Dirty Machine Learning Co

"you can trust us!"

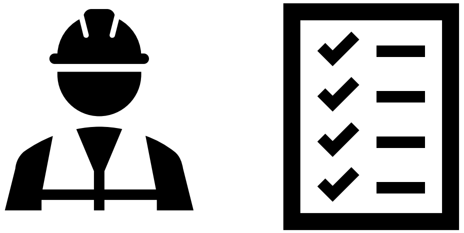
"can we allow this product?"

the authorities

Two ways of providing trust in plumbing



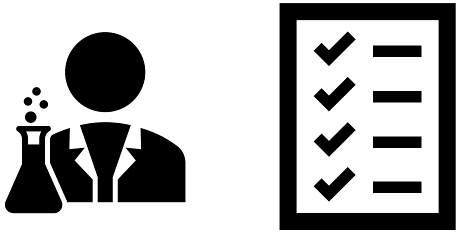
1 What did the plumber do?



2 Inspect the pipes

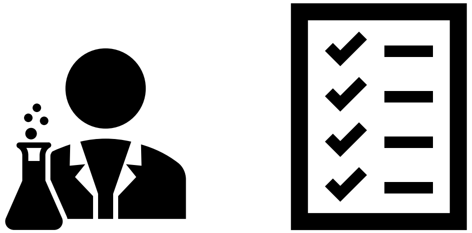
Trust in Machine Learning

Trust in the process



1 What did the modeller do?

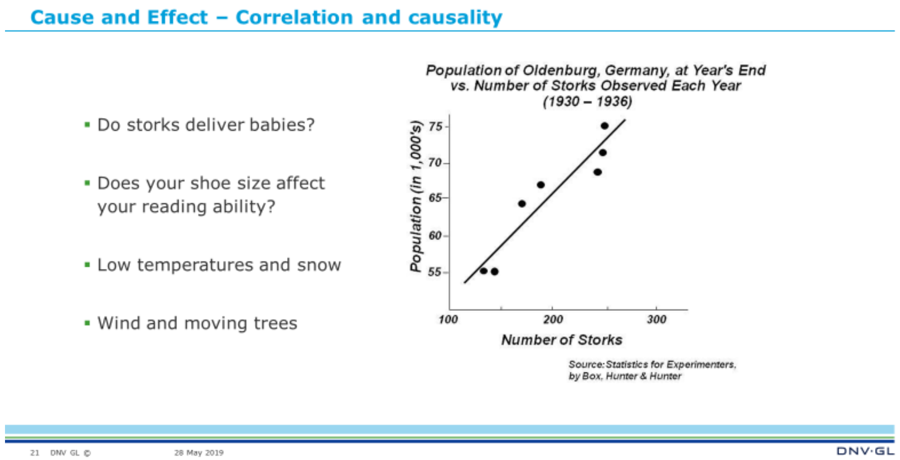
Trust in the model



2 Inspect the model

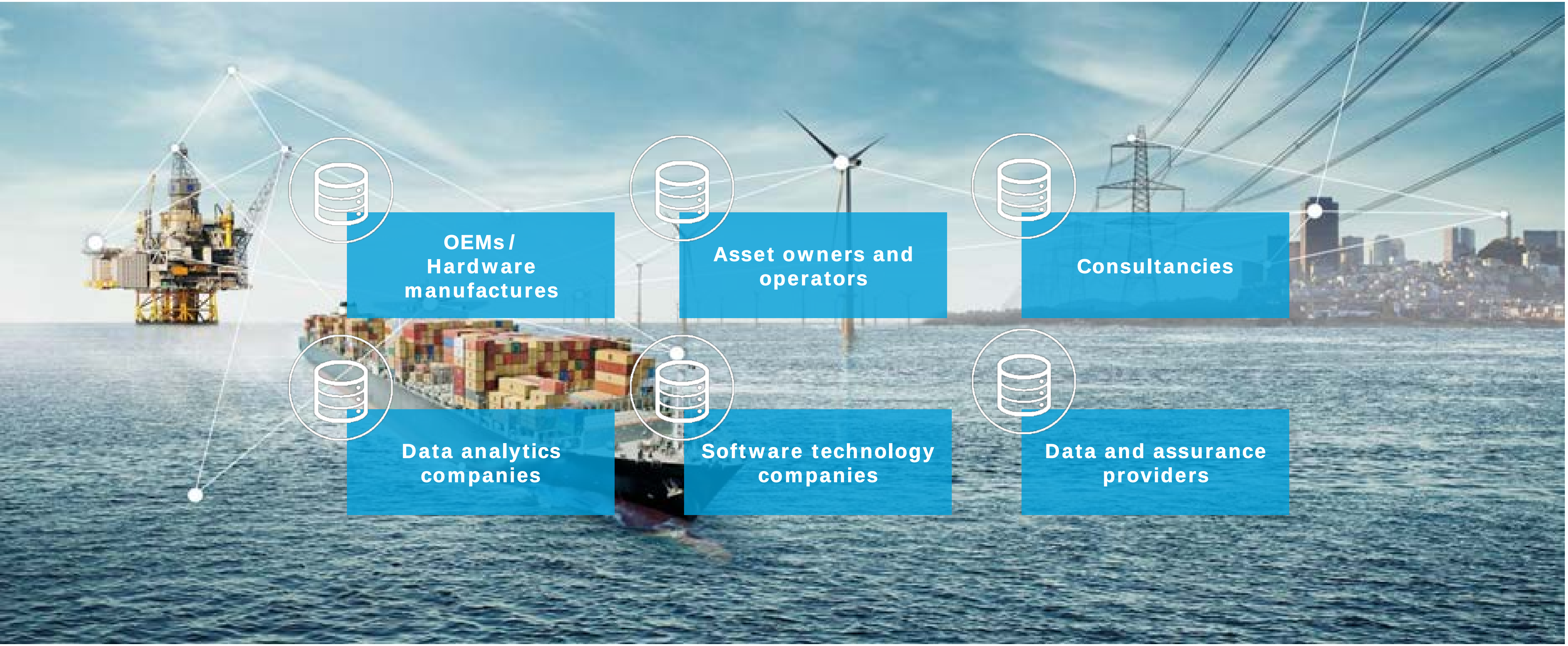
Pitfalls in Data Science and Machine Learning

- Data used to train the model is also used as test data
- Too few data
- Spurious or lack of relationship in data
- Simple is beautiful
- Correlation as a measure of relationship between data sets
- Overconfidence
- Time Series
- Violation of normality assumption
- Result interpretation



Example of DNV GL offerings to the Wind industry

Industrial platform players are emerging as a response - value propositions that mirror historical business models



Veracity - a trusted, value-unlocking ecosystem

PROVIDERS

Asset owners

+

Manufacturers

Assurance providers

Other data providers

MULTI-SIDED INDUSTRY DATA PLATFORM

Quality assessment

Data fabric (private preview)

My data

Marketplace

My services

Developer's toolbox

CONSUMERS

Asset owners

+

Manufacturers

Regulators

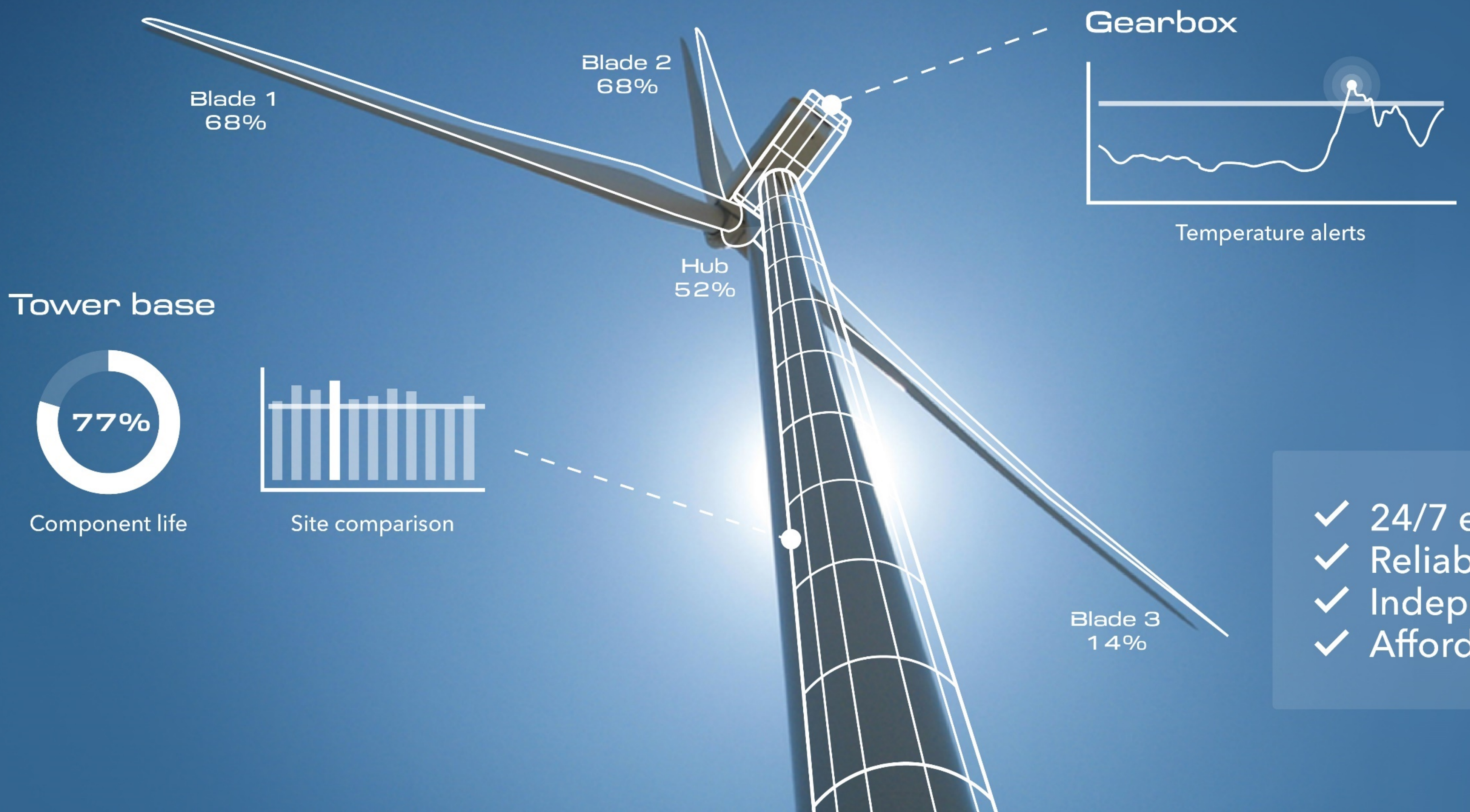
Insurance

Other stakeholders

DEVELOPERS, ANALYTICS AND SOFTWARE PROVIDERS

WINDGEMINI

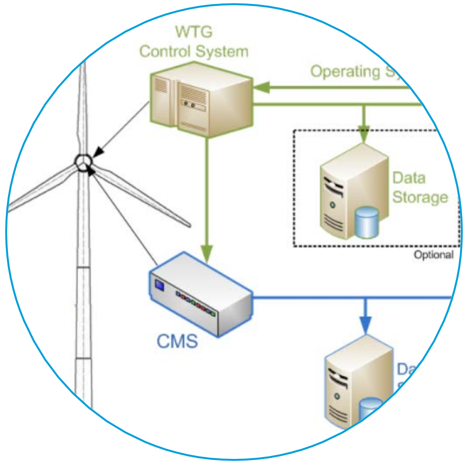
A digital twin for your wind farm by the world's renewable energy expert.



- ✓ 24/7 easy access
- ✓ Reliable
- ✓ Independent
- ✓ Affordable

What is WindGEMINI?

- A digital twin to deliver engineering knowledge to our customers in an efficient and accessible way



Universal data interface

- Uses standard turbine data
- No need for additional sensors
- OEM agnostic
- "Near" real time

Plug in algorithms

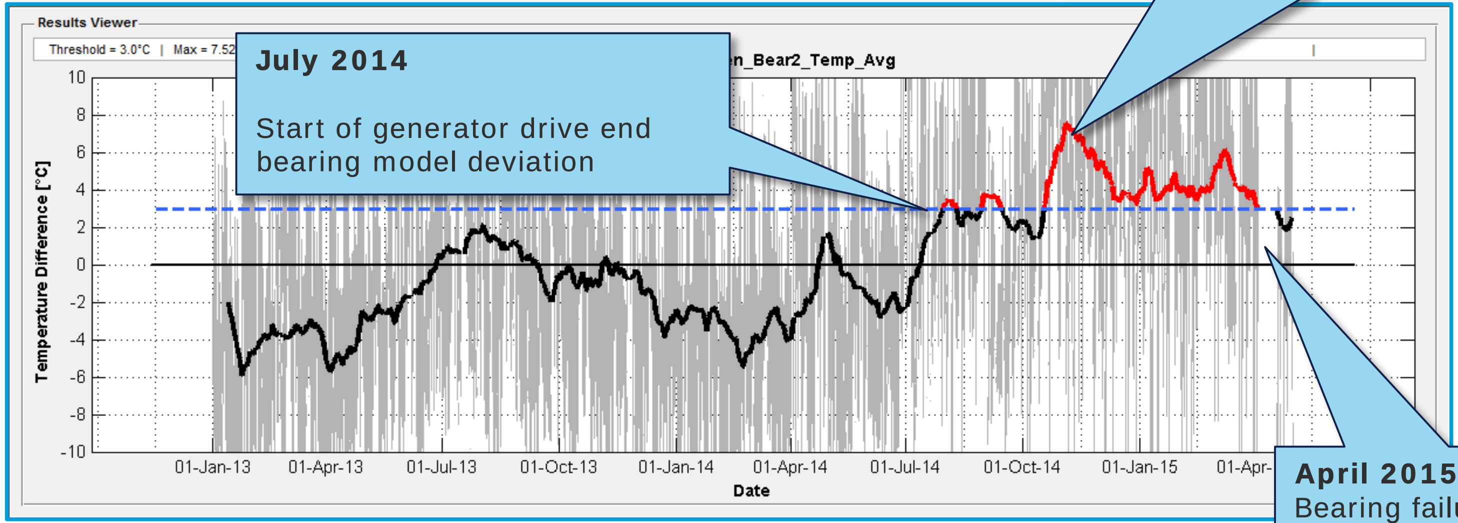
- DNV GL knowledge and experience
- Predict failures
- Analyse performance
- Indicate asset condition and value

Web-based interface

- Accessible 24/7
- Automated alerts
- "Analyst"/"asset manager" views
- Better, faster decision-making

Case study – Generator drive end bearing

- Traditionally managed wind farm: ‘Run to failure’ maintenance strategy
- SCM applied but **without** intervention



November 2014

Medium confidence alert raised, but no action was taken

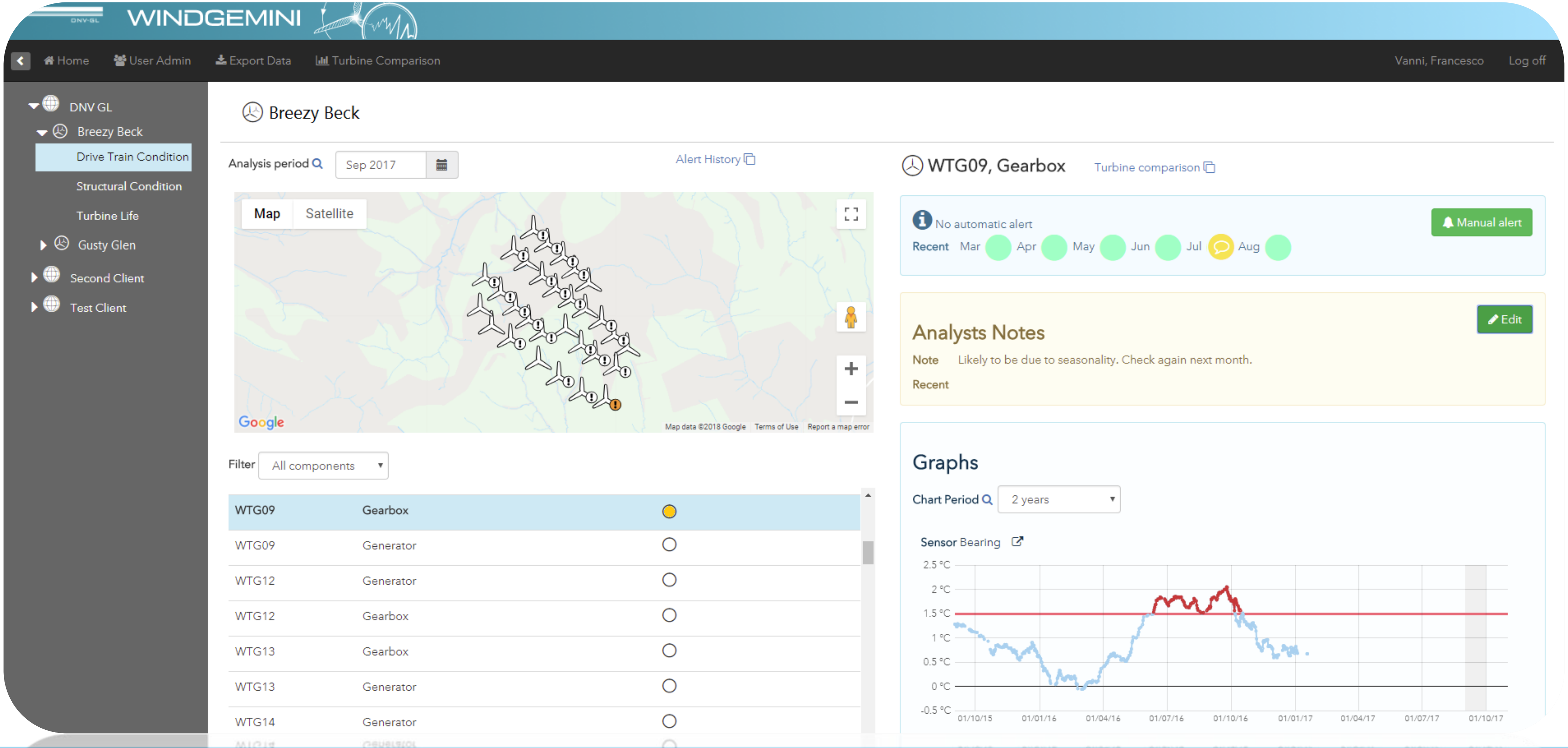
July 2014

Start of generator drive end bearing model deviation

April 2015
Bearing failure and full generator replacement was required: total of 15 days downtime

- Planned bearing replacement estimated at only 2 days downtime
- Estimated preventable revenue loss of £15k. Estimated generator cost £80k.

Drivetrain Integrity Monitor in WindGEMINI



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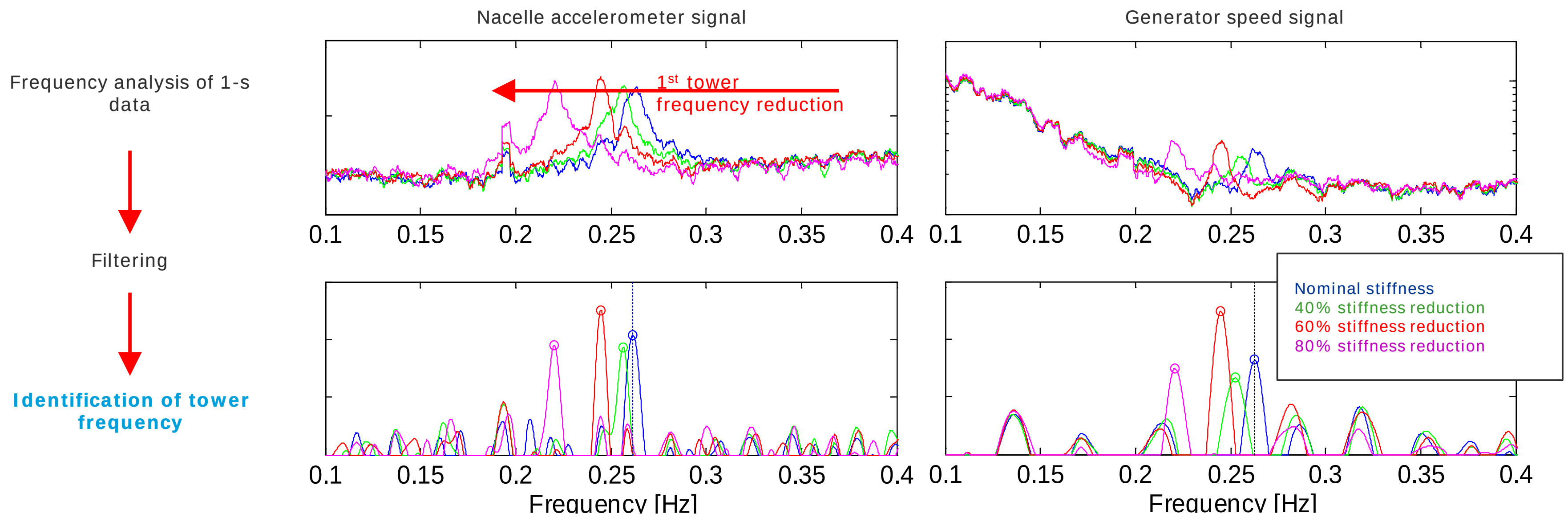
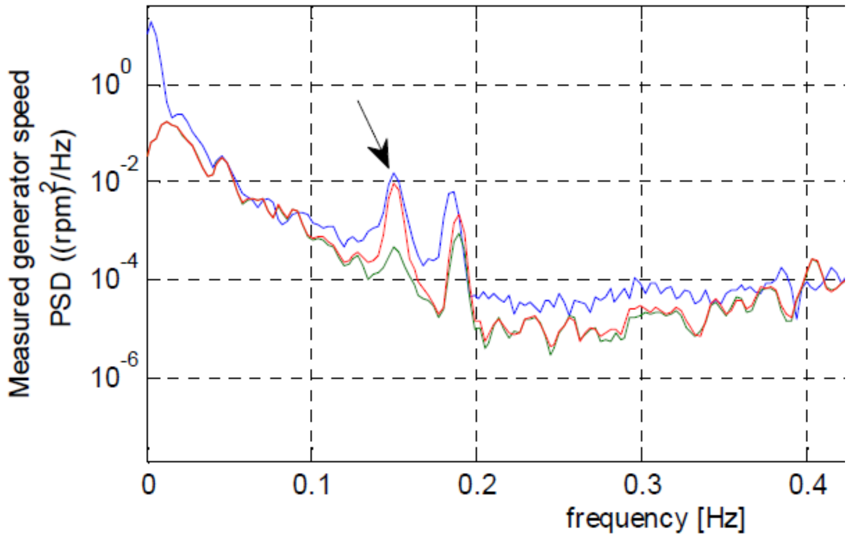
Structural Integrity Monitor

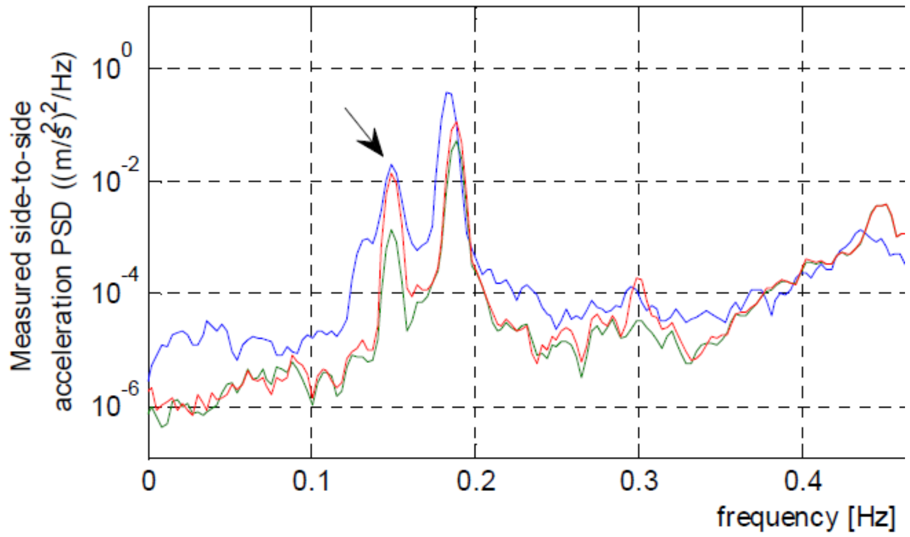
- Analysis of 1s SCADA allows tracking of tower & rotor frequency
- A convolution filter identifies frequency and energy levels of the main peaks
- Frequency analysis can identify a number of issues:
  - Shifts in foundation stiffness (degradation)
  - Rotor imbalance
  - Pitch misalignment



Case study – identification of rotor imbalance

- 2015 study on soft-tower turbines
- T1 autospectra shows more energy than T2 (and other turbines) at the rotor frequency
- Speed / side-side acceleration points to aerodynamic (pitch) imbalance
- Autospectra were matched by modelling a 2° pitch misalignment
- Inspections confirmed a 1.8° pitch misalignment, later corrected





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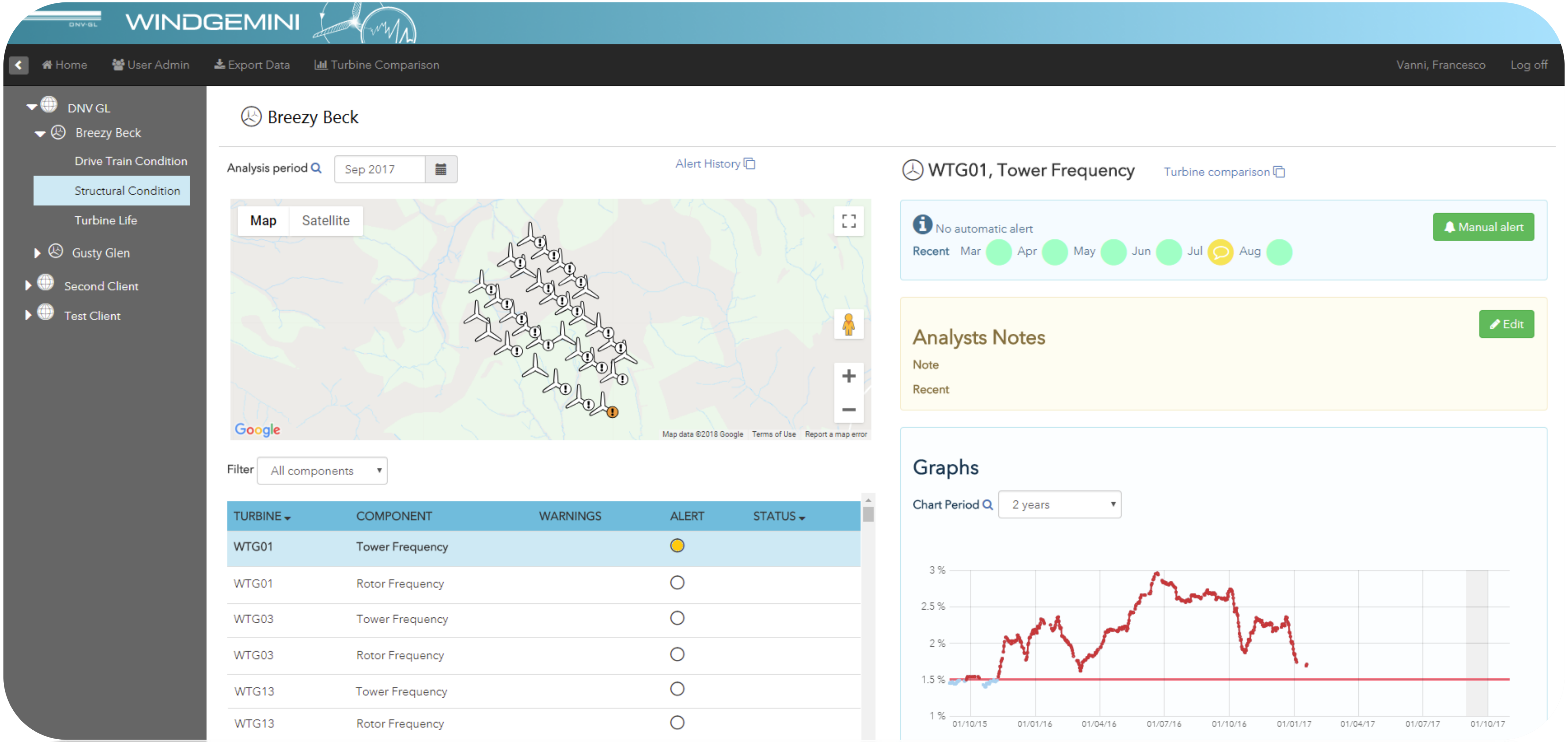
Structural Integrity Monitor in WindGEMINI



www.dnvgl.com

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