Challenges and Opportunities for AI and Data analytics in Offshore wind

Ravi Pandit

University of Exeter

Contents

Academic Profile

RESEARCH FELLOW, UoE (2020 – PRESENT)

- Closely working with **Alan Turing** Fellows (internally and externally) to develop interdisciplinary research ideas (e.g., Energy, Transport, policy and so on) in collaboration with domain experts around the university, and to underpin early-stage studies leading to future bids for research funding.

RESEARCH ASSOCIATE, UoS (2019 – 2020)

- Worked as a Research Associate in the Department of Naval Architecture, Ocean and Marine Engineering. This post relates to the EU funded ROMEO (Reliable OM decision tools and strategies for high LCoE reduction on offshore wind) project that includes the large number of Industrial partners such as Siemen Gamesa, Adwen, RAMBOLL.

Marie Curie Researcher , UoS (2016 – 2019)

- Worked on AWESOME project where I developed new novel techniques for extensive SCADA data analysis and condition monitoring based on machine learning algorithms to enhanced reliability, minimize downtime and reduce O&M costs.

Visiting Researcher, UCLM, Spain (2018 – 2018)

- Worked as a visiting researcher at the Renewable Energy Research Institute, Universidad de Castilla-La Mancha (UCLM), Spain. During this visit, I worked with interdisciplinary teams (includes academics and industries) in a complex wind turbine condition monitoring problems that lead to improving the capabilities of algorithms to predict the failure quickly without any false positives.

Visiting Researcher, Wood plc (2016 – 2017)

- Worked closely related to wind resource assessment in which in-depth analysis of large SCADA dataset involves such as wind data gathering, data analyses, energy estimation using machine learning techniques.

Assistant Professor (2011-2016)

- Worked Assistant Professor at the Jadavpur University (IEE) and Vellore Institute of Technology Vellore School of Electrical Engineering) .

UCLM UNIVERSIDAD DE CASTILLA-LA MANCHA

University of Strathclyde Glasgow

UNIVERSITY OF EXETER

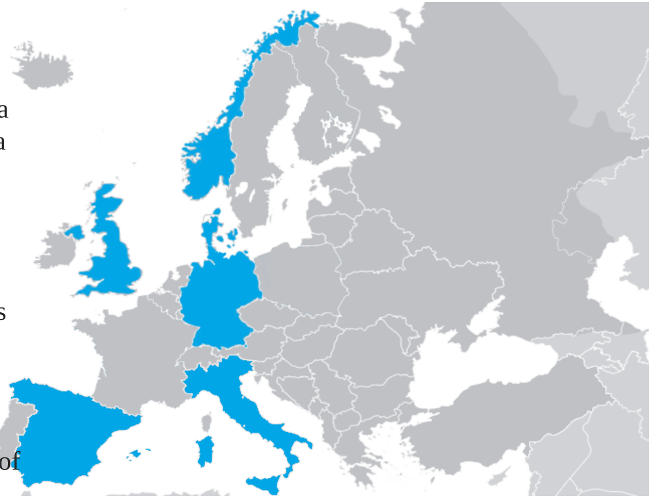
DTU Technical University of Denmark

TUDelft

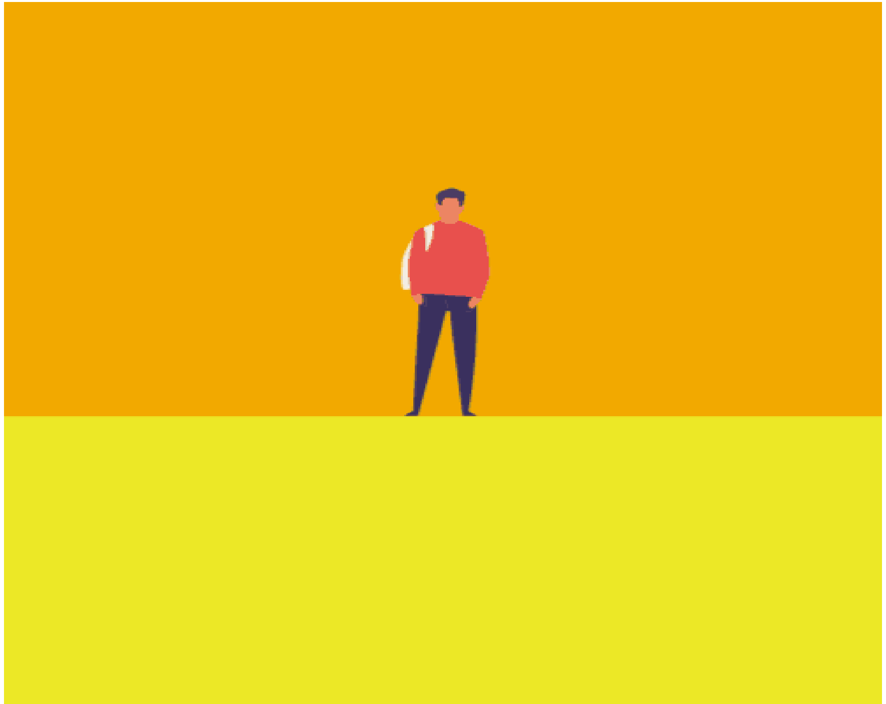
Loughborough University

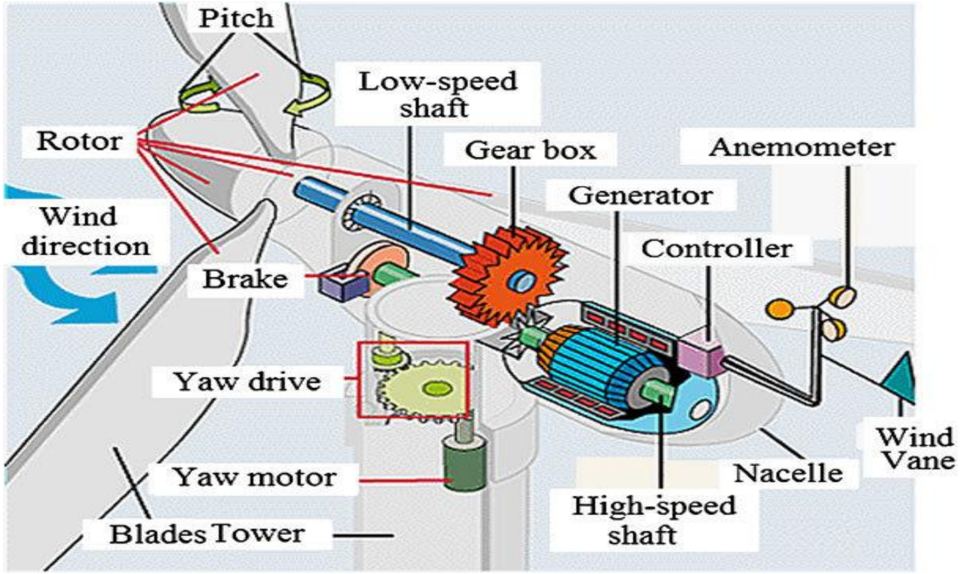
sgurr energy

RAMBOLL



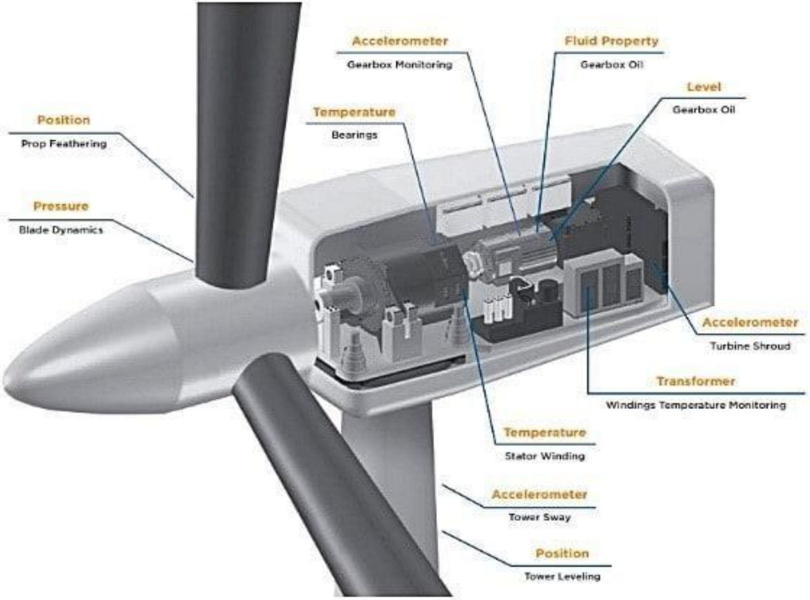
Overview of wind turbines

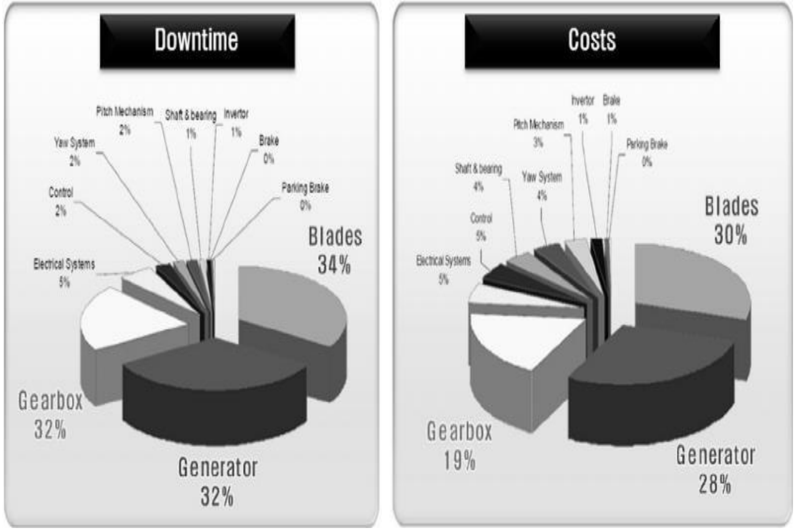




A group of wind turbines is called a wind farm. On a wind farm, turbines provide bulk power to the electrical grid. These turbines can be found on land (onshore) or at sea (offshore).

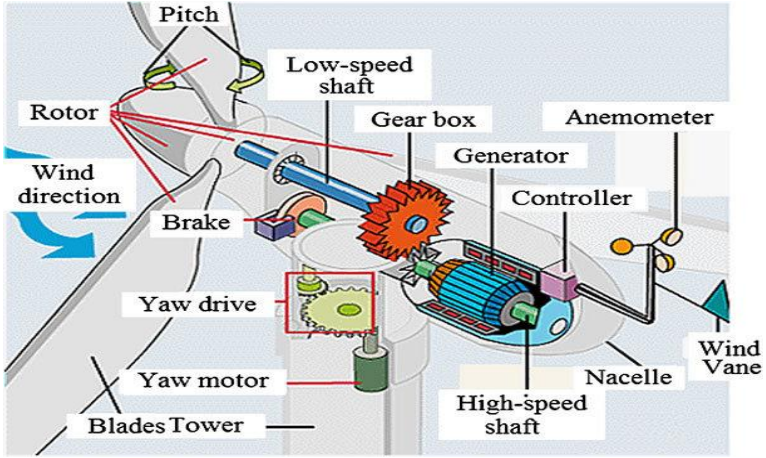
Motivation

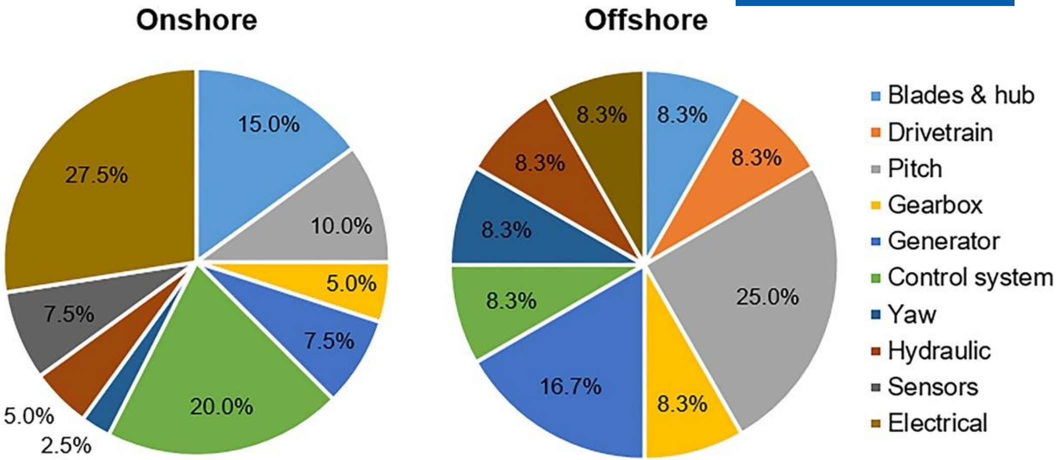




Unexpected equipment failure in a system can interrupt the production schedule and lead to costly downtime that can impact your bottom line significantly.

Challenges: Catastrophic failures



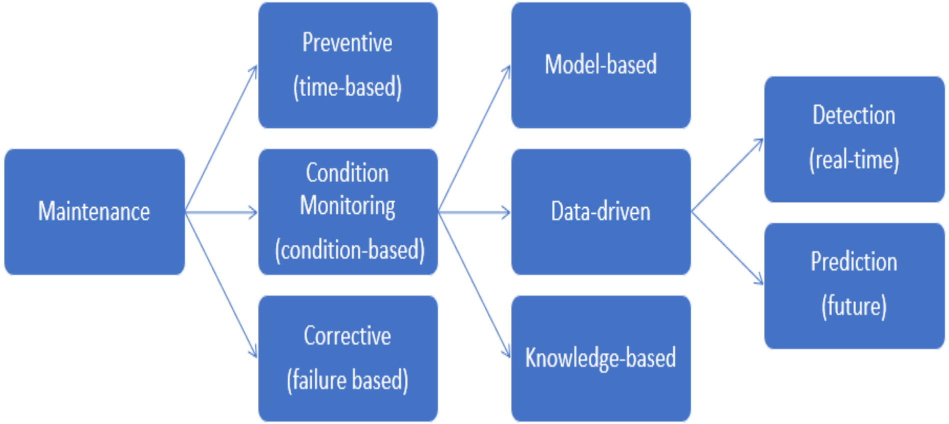


Critical subassemblies in terms of failure rate

- ✓ Catastrophic failures causes significant downtime and high maintenance costs.
- ✓ Dealing with big data: high computation costs and high pre-processing resources
- ✓ Applications of data-driven technologies still limited to real worlds.

Algorithms and Components Failures

Category A	Category B	Category C
1. Catastrophic blade failure	1. Cracks in blades	1. Controller failure
2. Catastrophic hub failure	2. Dirt/ice built up on blades	2. Hydraulic system failure
3. Main bearing failure	3. Hub spinng on shaft	3. Mechanical brake failure
4. Main shaft failure	4. Blade pitch fault	4. Pitching system failure
5. Gearbox failure	5. Shaft misalignment	
6. Shaft-gearbox coupling failure	6. Yaw fault	
7. Generator failure	7. Cable twist	
8. Tower failure	8. Error in wind speed/direction measurement	
9. Foundation failure		
10. Metrological system failure		
11. Premature brake activation		
12. Electrical system failure		



What is Predictive maintenance?

Predictive maintenance is a proactive maintenance strategy that uses condition monitoring tools to detect various deterioration signs, anomalies, and equipment performance issues. Based on those measurements, the organization can run pre-built predictive algorithms to estimate when a piece of equipment might fail so that maintenance work can be performed just before that happens.

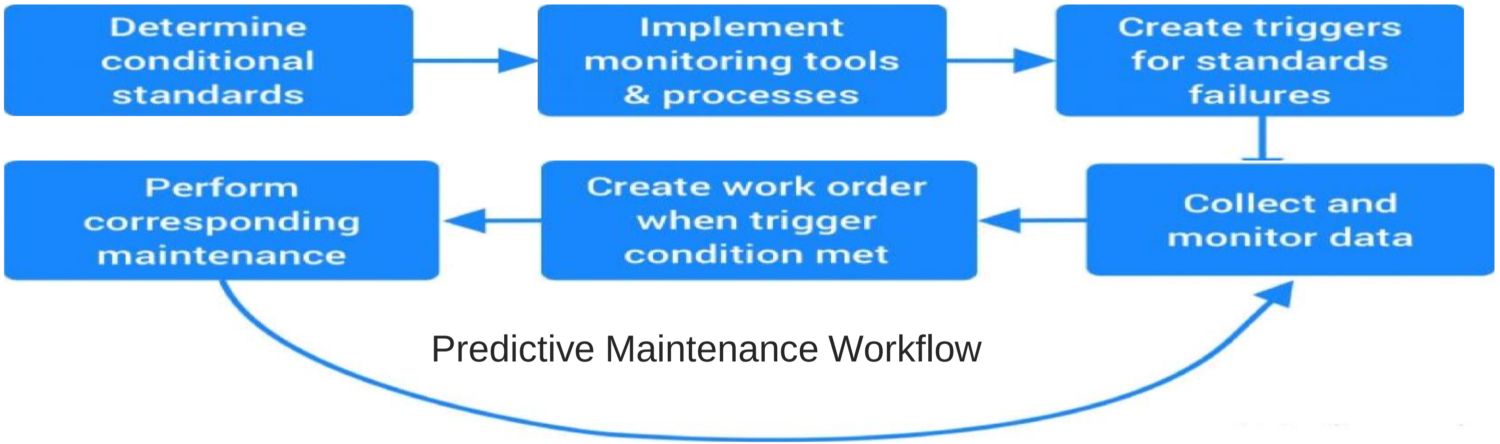
- The goal of predictive maintenance is to optimize the usage of your maintenance resources. By knowing when a certain part will fail, maintenance managers can schedule maintenance work only when it is actually needed, **simultaneously avoiding excessive maintenance and preventing unexpected equipment breakdown**.

- **When implemented successfully, predictive maintenance lowers operational costs, minimizes downtime issues,** and improves overall asset health and performance.

Predictive maintenance Vs Preventive Maintenance

Predictive Maintenance (PdM) - a maintenance strategy based on measuringequipment condition in order to predict whether failure will occur during some future period, thus permitting the appropriate preventive actions to be implemented to avoid the consequences of that failure.

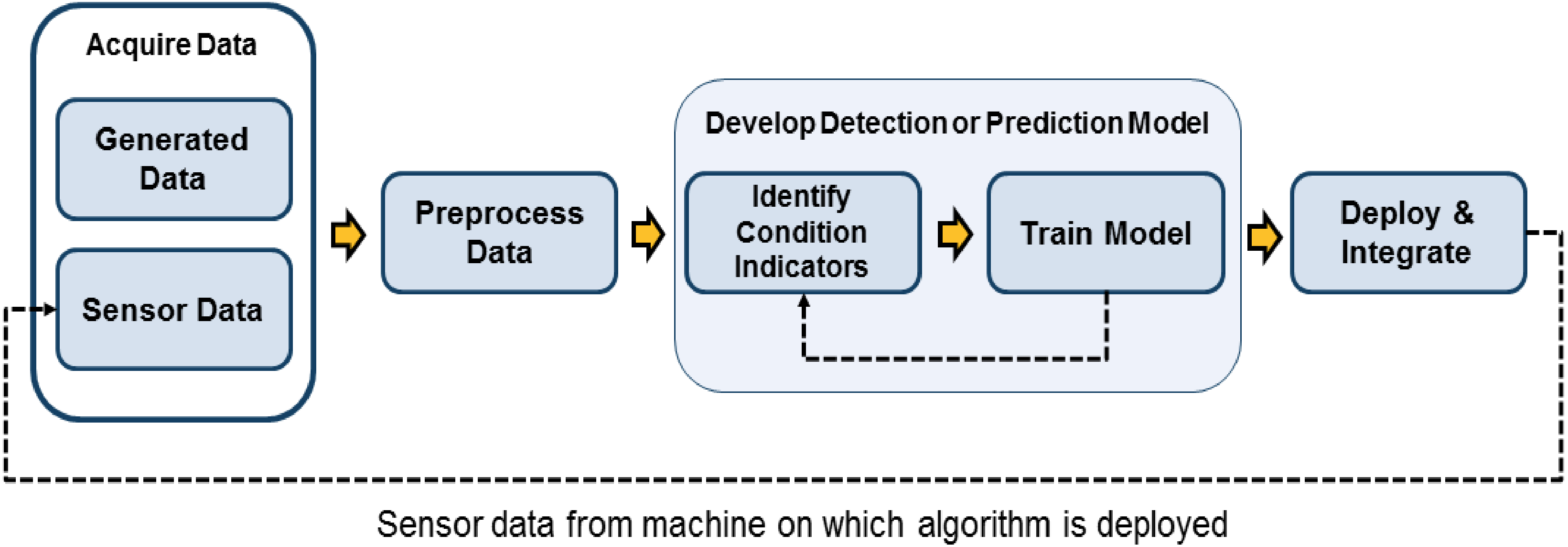
Preventive Maintenance (PM) – a maintenance strategy designed to prevent anunwanted consequence of failure including condition-directed, time-directed, interval-directed, and failure finding tasks.



Predictive Maintenance Workflow

Applying predictive algorithms

- The most important part of predictive maintenance (and arguably the hardest one) is building predictive (a.k.a prognostic) algorithms.
- The more variables you can use, the more accurate your models will be. This is why building predictive models is an iterative process.



Predictive Or Corrective ?

	Predictive Maintenance	Corrective Maintenance
Description	It is carried out at predetermined intervals. It covers multiple types of maintenance done before a failure has occurred. It aims to reduce the probability of breakdown or degradation of a piece of equipment.	With corrective maintenance, issues are ‘just in time. It is carried out followi detection of an anomaly. It is aimed at catching and fixing problems they happen.
Advantages	Reduces incidents of operating fault and eliminates unplanned shutdown time, having less impact on the production.	It gives technicians the possibility to perfor interventions without delay. As issues are found just-in-time, it r emergency repairs and increases employee Maybe cost-effective until catastrophic faul
Disadvantages	Investment required for maintenance program is greater than the cost of downtime and repair in case of faults in most cases.	Unplanned corrective maintenance can get as it can lead to costs that could not hav anticipated.

Limitation of Predictive maintenance

- Requires condition-monitoring equipment and software to implement and run.
- You need a specialized set of skills to understand and analyse the condition-monitoring data
- High upfront costs
- Can take a while to set up and implement.

Is Predictive maintenance worth doing?

Predictive maintenance strategy should be proportional to failure consequences:

-Safety consequences: We must do whatever it takes to prevent these

-Operational consequences: Its probably worth some effort to prevent these

- Economic consequences: There's no reason to try to prevent these; the optimum maintenance strategy is "run to failure"

Alternatives to Predictive maintenance

Time-directed maintenance (TDM)

Attempts to avoid failures by retiring, replace or overhauling components at specific age.

Condition-directed maintenance (CDM)

Attempts to avoid failures by monitoring component condition to detect potential failures before they became catastrophic failures.

Condition monitoring

By definition, condition monitoring is a process of monitoring the performance of a machine, in order to identify potential changes which are indicative of a developing fault before machine reaches a stage where catastrophic damage occurs.

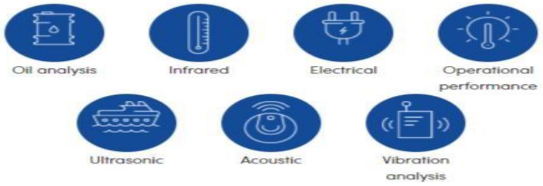
Advantages

- CBM is performed while the asset is working, which lessens the chances of disruption to normal operations
- Reduces the cost of asset failures
- Improves equipment reliability
- Minimizes unscheduled downtime due to catastrophic failure
- Minimizes time spent on maintenance
- Minimizes overtime costs by scheduling the activities
- Minimizes requirement for emergency spare parts
- Optimizes maintenance intervals (more optimal than manufacturer recommendations)
- Improves worker safety
- Reduces the chances of collateral damage to the system

Disadvantages

- Condition monitoring test equipment is expensive to install, and databases cost money to analyze
- Cost to train staff—you need a knowledgeable professional to analyze the data and perform the work
- Fatigue or uniform wear failures are not easily detected with CBM measurements
- Condition sensors may not survive in the operating environment
- May require asset modifications to retrofit the system with sensors
- Unpredictable maintenance periods

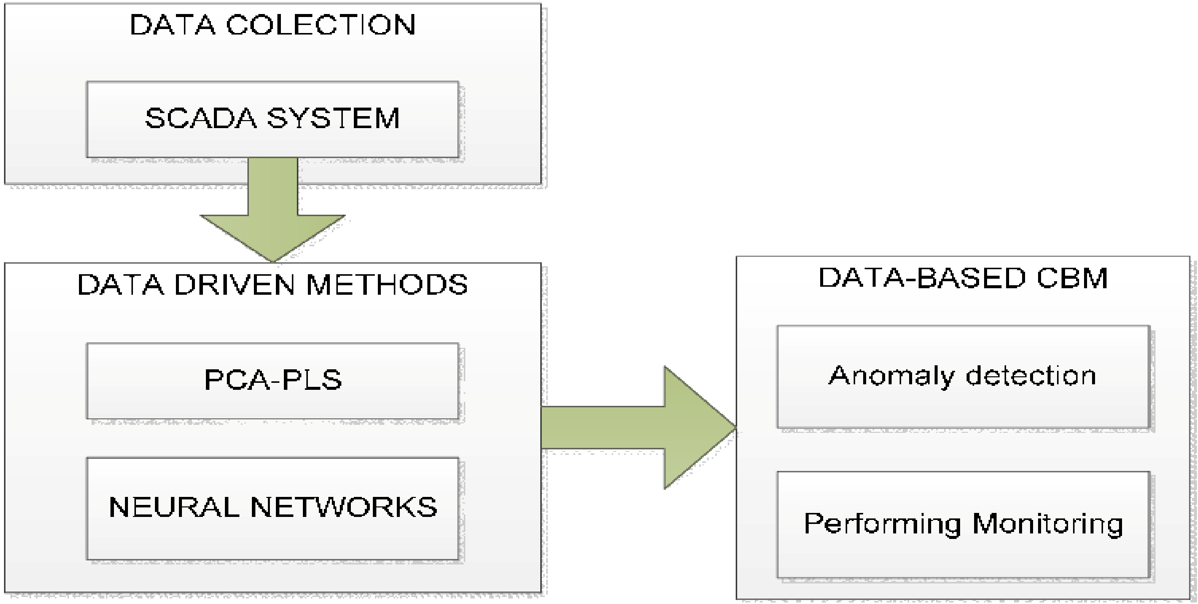
Types of condition based maintenance



There are various types of condition-based monitoring techniques. Here are a few common examples:

- Vibration analysis: Rotating equipment such as compressors, pumps and motors all exhibit a certain degree of vibration. As they degrade, or fall out of alignment, the amount of vibration increases. Vibration sensors can be used to detect when this becomes excessive.
- Infrared: IR cameras can be used to detect high-temperature conditions in energized equipment
- Ultrasonic: Detection of deep subsurface defects such as boat hull corrosion
- Acoustic: Used to detect gas, liquid or vacuum leaks
- Oil analysis: Measures the number and size of particles in a sample to determine asset wear
- Electrical: Motor current readings using clamp on ammeters
- Operational performance: Sensors throughout a system measure pressure, temperature, flow etc.

SCADA data-based condition monitoring



ROMEO (Reliable O&M decision tools and strategies for high LCoE reduction on Offshore wind), is seeking to reduce offshore O&M costs through the development of advanced monitoring systems and strategies, aiming to move from corrective and calendar based maintenance to a condition based maintenance, through analysing the real behaviour of the main components of wind turbines (WTGs).

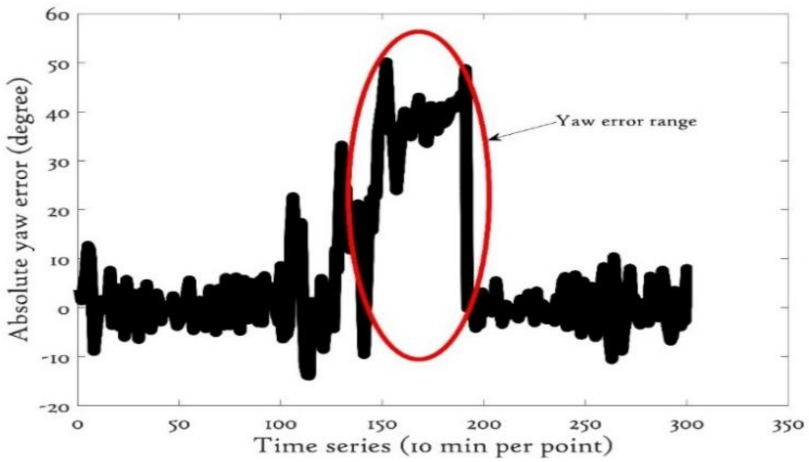
- ✓ To develop better O&M planning methodologies of wind farms for maximizing its revenue
- ✓ To optimise the maintenance of wind turbines by prognosis of component failures and
- ✓ To develop new and better cost-effective strategies for Wind Energy O&M.

Condition monitoring

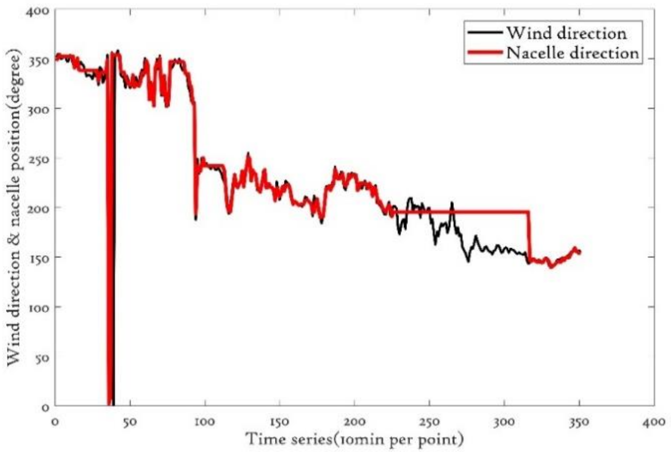
Yaw Misalignment – A Case Study

Yaw failures are **catastrophic in nature** cause high economic loss due to low power generation. Recent statistical figures indicating downtime caused by **yaw failures comprised 13.3%** of **the total downtime**, while the **yaw system failure rate comprised 12.5%.** The cost associated with such failures is high due to resulting unplanned maintenance and causing annual energy production (AEP) **loss up to 2%**, resulting in **40,000 GBP/ yr**, revenue loss for the wind farm project.

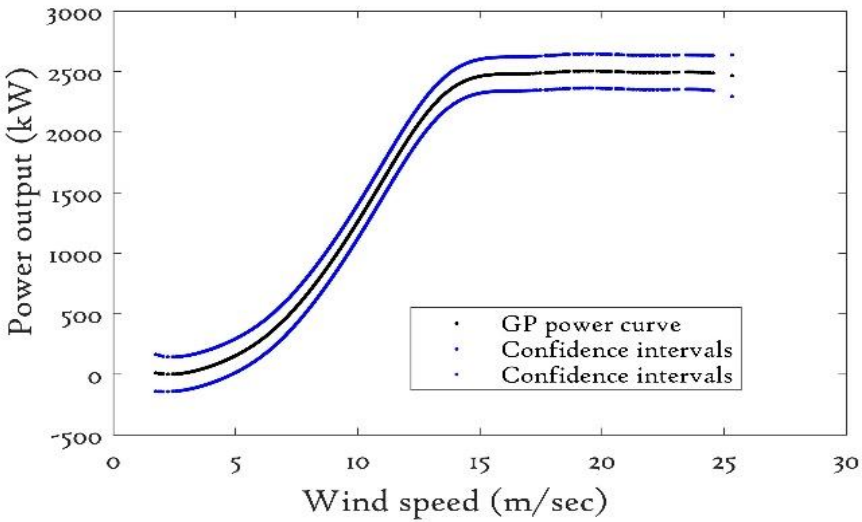
TimeStamp	Wind speed (Avg.) m/sec	Power (Avg.) kW	Ambient temp (Avg.) ℃	Atmospheric pressure (Avg.) mbar	Rotor speed (Avg.) m/sec	Blade pitch angle (Avg.) ℃
12/ 03/2009 10:00:00	5.05	270.93	7.44	986.35	9.57	-0.99
12/ 03/2009 10:10:00	5.07	230.45	7.85	986.45	8.75	-0.99
12/ 03/2009 10:20:00	6.09	150.72	7.90	986.47	7.98	-0.99
12/ 03/2009 10:30:00	6.10	255.20	8.40	986.55	9.30	-0.99
12/ 03/2009 10:40:00	6.15	240.15	8.80	986.58	8.35	-0.99



Absolute yaw error in time series

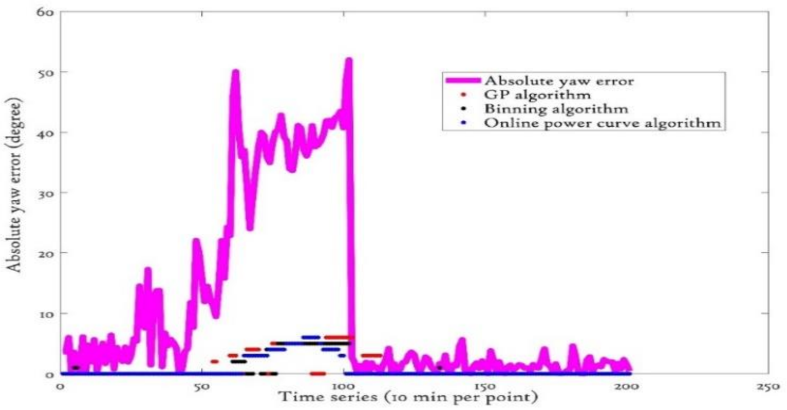


yaw misalignment via wind direction and nacelle direction in time series



Unhealthy data due to yaw misalignments will be assessed in terms of a probabilistic approach where each new data point is compared with the constructed GP reference power curve and if these data points lie outside of the confidence intervals of GP reference power curve then this indicates anomalous behavior and possible fault

Using the GP algorithm, an alarm would have been raised at 22:30 on 14/04/2009, just 1.5 hrs after the start of the yaw fault at 21:00 on 14/04/2009.



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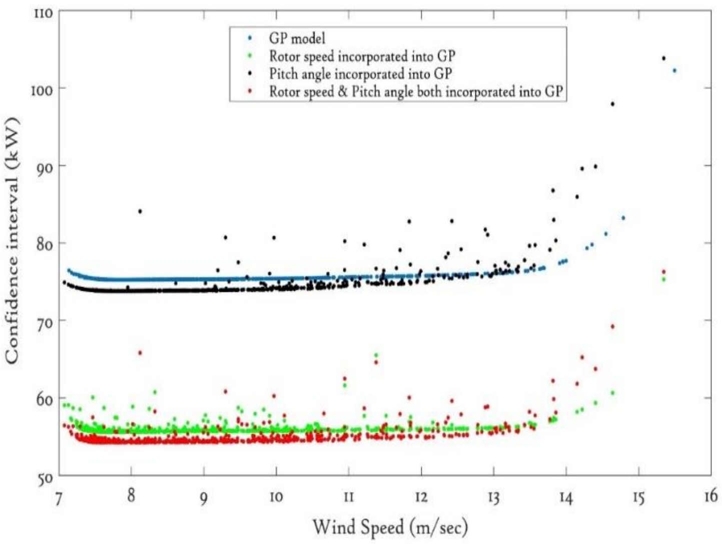
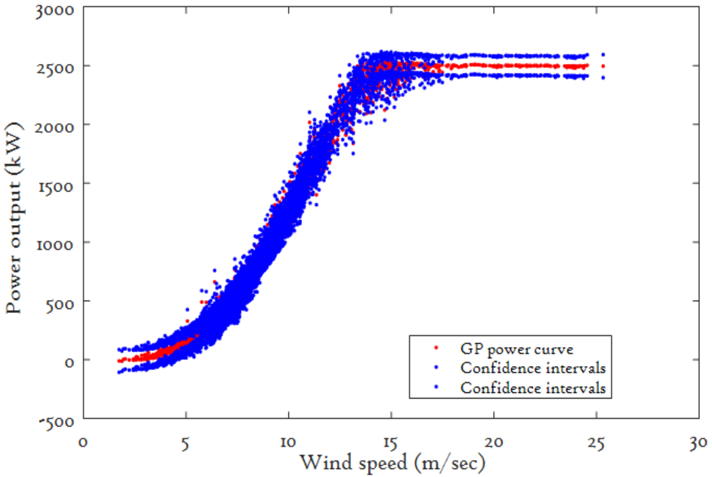
Model	Alarm detected	Time taken to identify the fault
Online power curve model	3:00 on 15/4/2009	6 hours
Probabilistic assessment using binning	00:50 on 15/4/2009	~ 4 hours
Probabilistic assessment using GP	22:30 on 14/4/2009	1.5 hours

R. K. Pandit and D. Infield, "SCADA-based wind turbine anomaly detection using Gaussian process models for wind turbine condition monitoring purposes," in ***IET Renewable Power Generation***, vol. 12, no. 11, pp. 1249-1255, 20 8 2018, doi: 10.1049/iet-rpg.2018.0156.

Big data features engineering





Ravi Kumar Pandit, David Infield and Athanasios Kolios. Gaussian Process Power Curve Models Incorporating Wind Turbine Operational Variables. Energy Reports, vol 6, 2020,pp.1658-1669, ISSN 2352-4847. doi:10.1016/j.egyr.2020.06.018.

TimeStamp	Wind speed (Avg.) m/sec	Power (Avg.) kW	Ambient temp (Avg.) ℃	Atmospheric pressure (Avg.) mbar	Rotor speed (Avg.) m/sec	Blade pitch angle (Avg.) ℃
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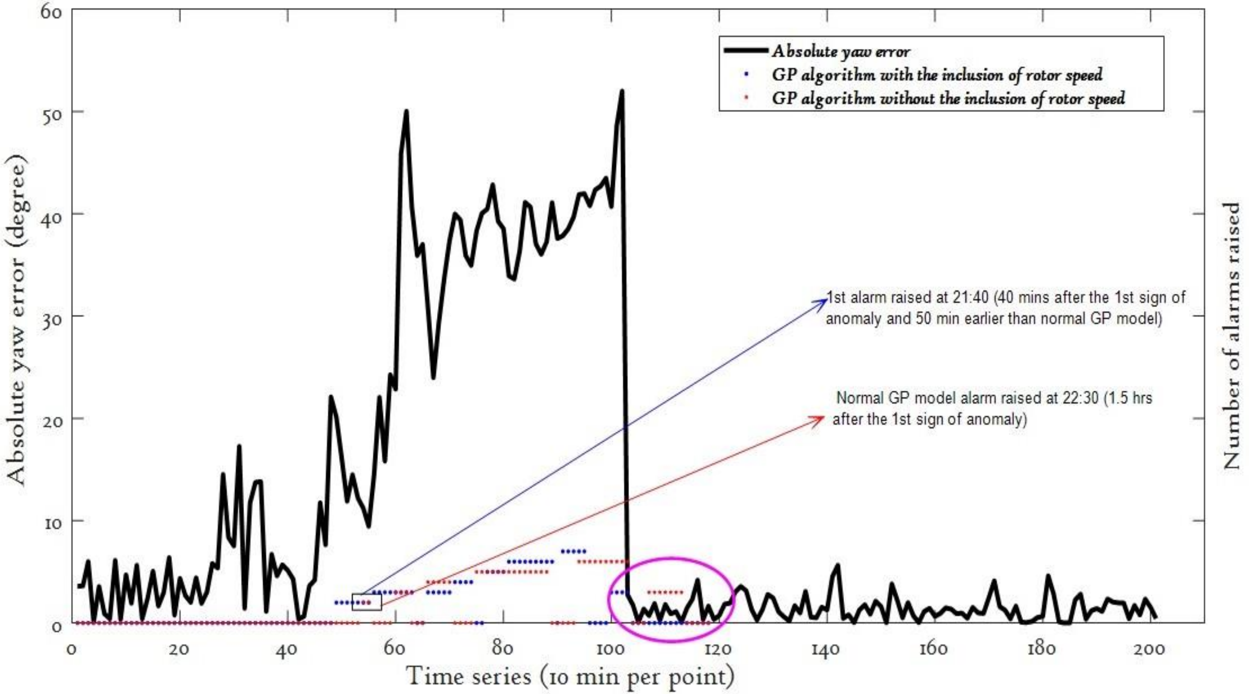
Early Failure detections



R. Pandit, D. Infield and T. Dodwell, "Operational Variables for Improving Industrial Wind Turbine Yaw Misalignment Early Fault Detection Capabilities Using Data-Driven Techniques," in *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1-8, 2021, Art no. 2508108, doi: 10.1109/TIM.2021.3073698.

Uncertainty Improvement

Importance of Air density for uncertainty quantification

WTs	SCADA datasets time period	Total number of data points	Average monthly temperature (℃)	Standard density (kg/m^3)	Mean absolute difference (kg/m^3)
A	1/02/2010 -28/02/2010	4032	-5.2775	1.225	0.102
B	1/08/2010 -31/08/2010	4400	29.7791	1.225	0.061

$$\rho = 1.225 \left[\frac{288.15}{T}\right]\left[\frac{B}{1013.3}\right]$$

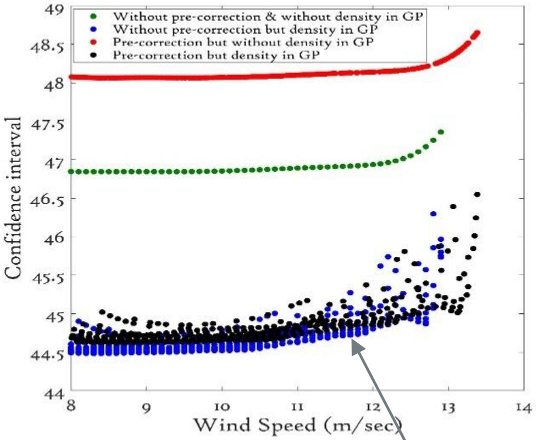
$$V_C = V_M \left[\frac{\rho}{1.225}\right]^{\frac{1}{3}}$$

The air density correction shall be applied when the site density differs from the standard value (1.225 kg/m^3) by more than 0.05 kg/m^3

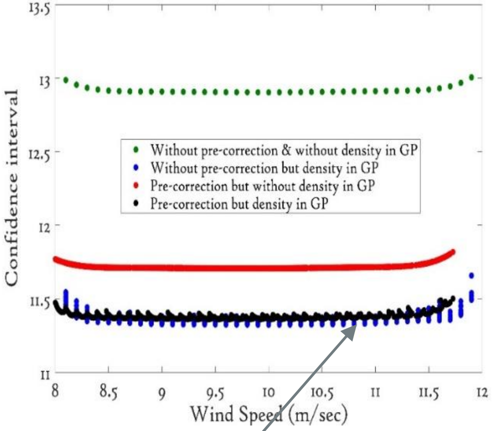
Site	Standard density	Mean absolute density difference	Total number of data points used
A	1.225	0.099	1114
B	1.225	0.062	1116

To limit the size of the data set, analysis will be restricted to the wind speed range of 8 to 14 m/s since the number of data points are sufficient within this range and also the number of data points resulting for sites A and B are almost the same.

ROMEO
AWESOME PhD'S IN WIND POWER O&M
NTNU Norwegian University of Science and Technology
Vestas
University of Strathclyde Glasgow



Uncertainty assessment in terms of confidence intervals for different air density approaches with limited data set for site A



Uncertainty assessment in terms of confidence intervals for different air density approaches with limited data set for site B

No pre-correction but with air density include within the GP model

Commercialised

Pandit, RK, Infield, D, Carroll, J. Incorporating air density into a Gaussian process wind turbine power curve model for improving fitting accuracy. ***Wind Energy***. 2019; 22: 302–315.

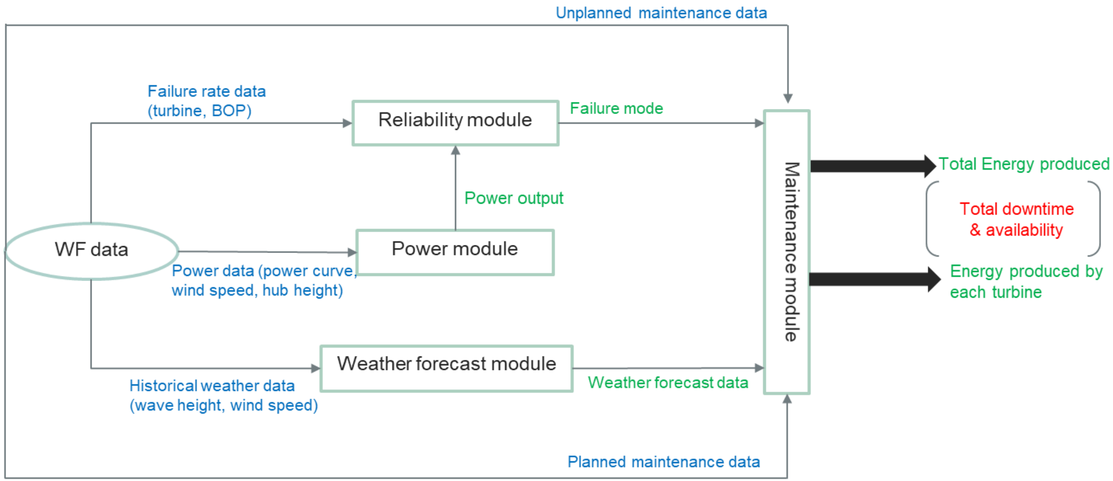
GP models	WT- A					WT-B				
	MAE	MSE	MAPE	RMSE	R^2	MAE	MSE	MAP E	RMS E	R^2
No pre-correction and air density not included in the GP model	18.012	568.075	9.439	23.834	0.878	5.196	43.094	2.469	6.564	0.982
No pre-correction but with air density include within the GP model	16.813	506.967	8.958	22.515	0.891	4.626	33.012	2.204	5.745	0.986
Pre-correction applied but without air density in the GP model	18.501	598.094	9.680	24.456	0.872	4.736	35.463	2.251	.955	0 .985
With pre-correction and air density included with the GP	16.868	510.016	8.990	22.583	0.891	4.648	33.344	2.215	5.774	0.986

Statistical measures of GP fitted models under different air density approaches

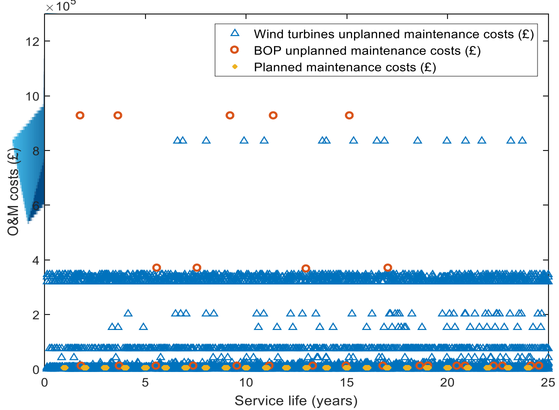
Data-Driven maintenance module

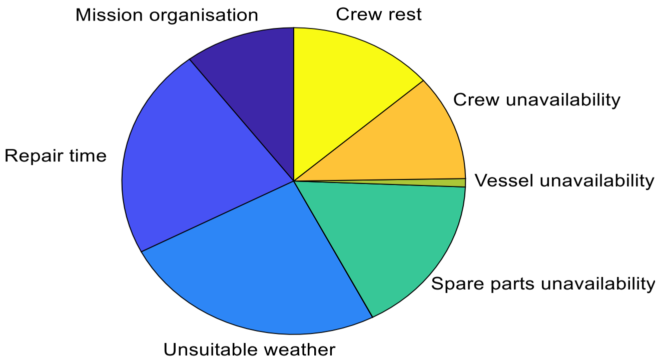
O&M module for offshore

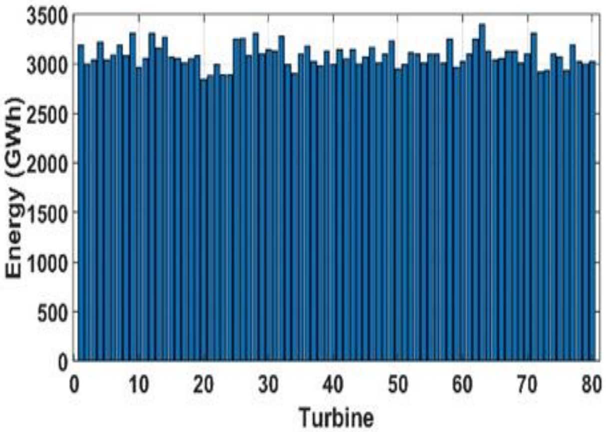
The financial appraisal of offshore wind farms is a demanding task which requires a number of factors to be considered in order to ensure that relevant KPIs are estimated in a meaningful way. Key elements of Capital expenditures (CAPEX), Operating expenditures (OPEX), Financial expenditures (FINEX) and the amount of energy production should be modelled through appropriate methods, based on sound assumptions. In addition, consideration of the service life emissions of renewable energy projects are meaningful so as to evaluate their actual contribution to sustainable development.

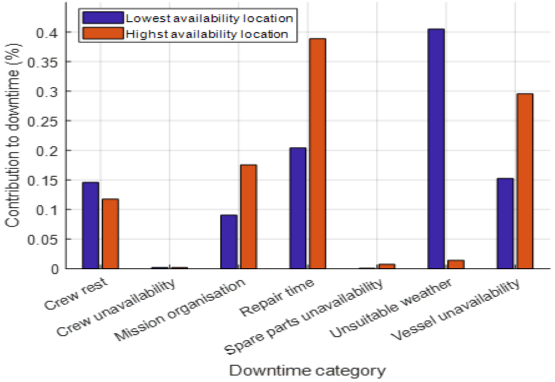


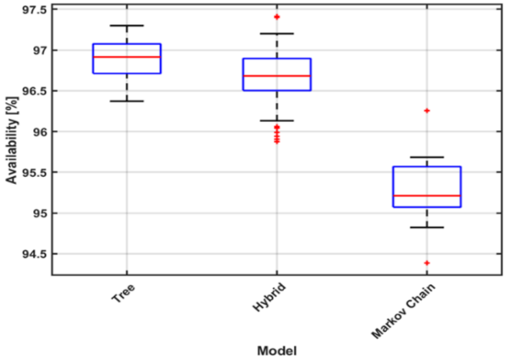
Athanasios Kolios, Julia Walgern, Sofia Koukoura, **Ravi Pandit** and Juan Chiachio-Ruano. openO&M: Robust O&M open access tool for improving operation and maintenance of offshore wind turbines. Proceedings of the 29th European Safety and Reliability Conference (ESREL), January 2020.
ISBN: 978-981-11-2724-3. doi:10.3850/978-981-11-2724-3_1134-cd.











O&M related outputs (Energy generated by each wind turbine in its whole life, Breakdown of windfarm downtimes, O&M costs throughout the service life of the wind farm, contribution of downtime categories to the highest and lowest availability locations, Monthly power production losses as a function of time for the location with coordinates, Sensitivity analysis of key design inputs)

Development stage

Mark Richmond, **Ravi Pandit,** Sofia Koukoura and Athanasios Kolios. Effect of weather forecast modelling uncertainty to the availability assessment of offshore wind farms. Submitted to **Renewable Energy** on October 2020. (**Journal**)

Ravi Pandit, Athanasios Kolios and David Infield. Data-driven weather forecasting models performance comparison for improving offshore wind turbine availability and maintenance. IET Renewable Power Generation , August, 2020. doi: 10.1049/iet-rpg.2019.0941.

Challenges

- Big data computational difficulty
- Data-driven classic problems
- Data availability
- Data security

Data Science/ML for Offshore Wind

Data analytics x

=

- Carbon footprint ↓
- Achieve EU net zero target sooner.
- Costs ↓

Future map for offshore wind

Digitalization of Offshore Wind

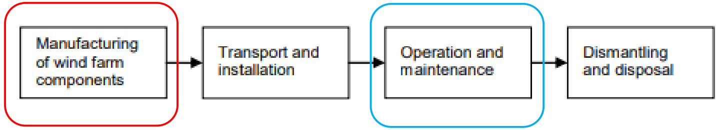
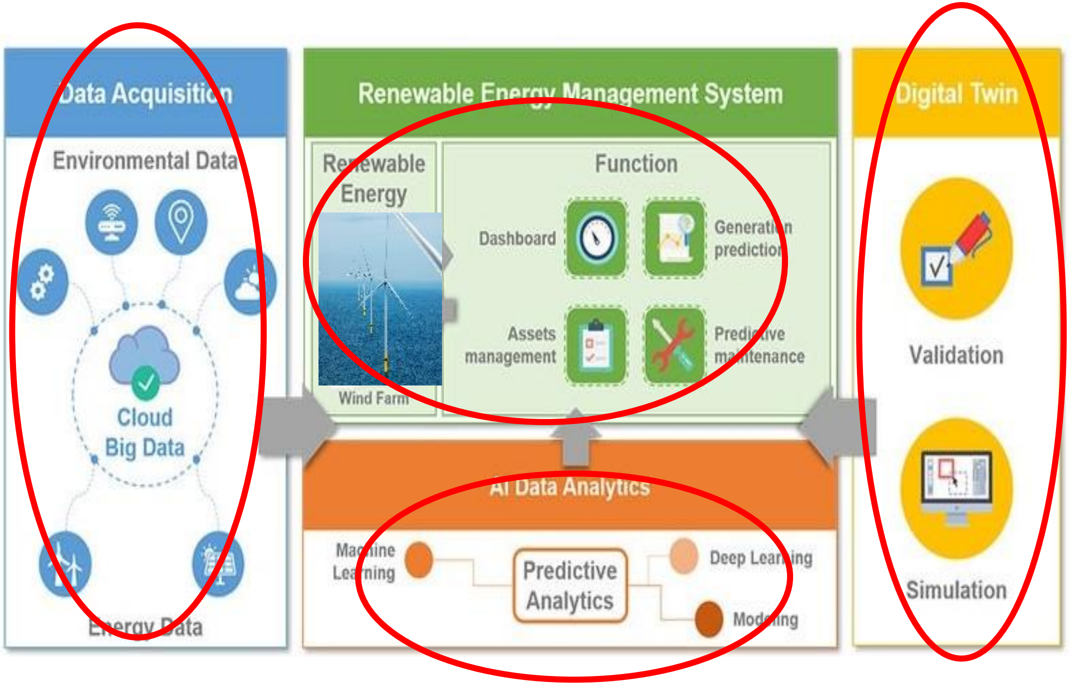


Fig: Life cycle of a wind farms

Objectives

- ✓ Logistics cost and transport cost
- ✓ Decision making process
- ✓ Automated health monitoring process
- ✓ Energy efficient Algorithm: space, time.
- ✓ Big data computation



Research Areas

Computer science

Engineering

Offshore Wind

data analytics

Cost-effective algorithms

data-driven models such as Machine learning and deep learning.

Forecasting & Prediction

Forecasting short-term, long-term: relevant parameters.

Real-time condition monitoring

Less human intervention, Avoid catastrophic damages .

Big Data analysis

data clustering, digital twins, Cloud computation, Correlation among big datasets.

Decommissioning & Asset life extensions

Near to end of warranty period, carbon foot prints.

Digitalisation

- **Decision making**
- **Minimising cost**
- **Risk & Reliability**
- **Big data computation**

Loughborough University

circe

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University of Strathclyde Glasgow

TU Delft

DTU Technical University of Denmark

Ingeteam

sgurr energy

RAMBOLL

IBERDROLA

ALSTOM

LAULAGUN bearings

DNV·GL

UPTIME ENGINEERING

SIEMENS Gamesa
RENEWABLE ENERGY

zabala
innovation consulting

CATAPULT
Offshore Renewable Energy

aee
Asociación Empresarial Eólica

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Adwen

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IBM Research | Zurich

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Any questions ?