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Report on Innovations

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ROMEO

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List of abbreviations

AI	Artificial Intelligence
API	Application Programming Interface
CM	Condition Monitoring
CMS	Condition Monitoring System
CNN	Convolutional Neural Network
COS	Cloud Object Store
DC	Direct Current
DT	Decision Trees
EU	European Union
FMEA	Failure Modes, Effects Analysis
FMECA	Failure Modes, Effects and Criticality Analysis
FMSA	Failure Mode Symptom Analysis
IEA	International Energy Agency
IT	Information Technology
KPI	Key Performance Indicator
LCoE	Levelised Cost of Energy
P-F	Potential Failure
ML	Machine Learning
MTTF	Mean Time to Failure
O&M	Operation and Maintenance
OEM	Original Equipment Manufacturer
OPEX	Operating Expenses
RF	Random Forest
RMS	Root Mean Square
RNA	Rotor Nacelle Assembly
SCADA	Supervisory Control and Data Acquisition
SHM	Structural Condition Monitoring
SQL	Structured Query Language
WF	Wind Farm
WP	Work Package
WT	Wind Turbine

1. Executive Summary

The past decade has seen a rapid increase in renewable project installation, due to the urgent need to combat climate change. The EU committed to global climate action under the Paris Agreement [cite] and further collective international action pledges were made during the Glasgow Climate Pact during COP26, nations are called upon to phase down unabated fossil fuels. At the time writing this report, the world is facing an unprecedented energy crisis.

Since the beginning of ROMEO project in 2017, there has been more than 12GW of new offshore installed capacity in Europe. At the end of 2021, there were 236GW of wind energy installed in Europe ,with 28GW being offshore [1]. At the same time, worldwide there was 743GW of wind installed, with 35 being offshore [2]. During 2021, the European Commission has tabled the Fit-for-55 package, a series of legislative proposals to deliver the EU's climate target of 55% emissions reduction by 2030. Based on that, the EU would need 453 GW of wind energy capacity by 2030 (374 GW onshore and 79 GW offshore). GWEC forecasts 235 GW of new offshore wind capacity will be installed over the next decade under current policies.

The growing annual installation rates of offshore wind turbines call for the need to reduce OPEX or TCO and improve availability of offshore wind farms. However, this growing installation rate comes with increase in digital information received from assets and an increase need for maintenance requirements and decision making. These maintenance decisions include:

- Scheduling of orders, personnel, transportation, and procedures
- Ensuring health and safety of everyone involved in the process
- Preventing equipment failure or degradation in order to maximise performance, reliability and safety

Digital technologies are continuously developing, and these include -but not limited to- computational power, connectivity, storage, data science algorithms and data engineering tools. . These developments are correlated with the emergence of Industry 4.0 (I4.0); a modern manufacturing system driven by information technology (IT) and achieving sustainable society [3]. I4.0 has remarkable potential to improve resource efficiency and maximise social, environmental and economic benefits. The opportunities and challenges of digitalisation and I4.0 towards achieving sustainable development have been widely discussed. The challenges are that these new methods require a transformation in business practices, promote rapid changes to industry's evolution and raise various concerns in terms of ethical and social controversies. But when digitalisation is responsibly harnesses, it comes with great opportunities for innovation, added value, greater insight and increase in efficiency. The enhanced analytical capacities and collaborative digital ecosystems could massively benefit the

[1] Wind energy in Europe: 2021 Statistics and the outlook for 2022-2026 https://windeurope.org/intelligence-platform/product/wind-energy-in-europe-2021-statistics-and-the-outlook-for-2022-2026/

[2] GWEC | Global Wind Report 2022 https://gwec.net/wp-content/uploads/2022/03/GWEC-GLOBAL-WIND-REPORT-2022.pdf

[3] Khan, Iqra Sadaf, Muhammad Ovais Ahmad, and Jukka Majava. "Industry 4.0 and sustainable development: A systematic mapping of triple bottom line, Circular Economy and Sustainable Business Models perspectives." Journal of Cleaner Production 297 (2021): 126655.

renewable energy sector. In the context of offshore wind farms, this could ultimately lead to significant savings in operational expenses (OPEX), improved decision making, enhanced safety and a reduction in the levelized cost of energy (LCoE).

Digitalisation in the wind energy industry has progressed in the past few years. There have been efforts to unify industry practices, like the International Energy Agency (IEA) Wind Task 43[4], but most efforts happen siloed within organisations and institutions. The wind energy, interdisciplinary as it is, would benefit from a collaborative initiative to expediate digitalisation potential and benefit all involved stakeholders from knowledge exchange and share of information. This has been the core foundation of the ROMEO project, which is an industry based consortium including large companies (manufacturers, operators, service providers, technology and AI specialists), SMEs and academia. ROMEO is an initiative backed by Horizon 2020 programme (call topic LCE-13-2016) which aims to develop advanced technological solutions that enable the Operation and Maintenance (O&M) costs of offshore wind power to be reduced.Partners have been chosen to cover the whole value chain, constituting an interdisciplinary group of experienced partners, providing of its expertise to cover the different fields required.

ROMEO's objectives are:

1. Greater reliability: Increase wind farm reliability and decrease the number of failures leading to downtime
2. Lifecycle enhancement: Increase the life time of key turbine components
3. O&M reduction in WT: Reduce the WT O&M costs through the reduction of resources required for annual inspections of the turbine
4. Foundation costs: Reduce the O&M costs associated to foundation through reduction in jacket substructure inspections

ROMEO has provided efficient and reliable condition-based maintenance and monitoring as well as decision support systems by early fault detection, diagnosis and prognosis models of components failures

This report summarizes the innovations developed throughout ROMEO project. The innovations contribute to increased reliability, lifecycle enhancements and reduction of costs of offshore wind farms, with the potential to unlock added value pathways towards improved O&M of offshore wind.

2. Introduction

In line with EU's climate targets, ROMEO (Reliable O&M Decision Tools and Strategies for High LCoE Reduction on Offshore Wind) project is endorsed by the EU Horizon 2020 programme. ROMEO's goals are to lower the LCoE of offshore wind energy through innovative technological solutions for O&M and advance the renewable energy sector.

[4] IEA Wind Task 43 https://www.ieawindtask43.org/

ROMEO is a 5-year project with an industry-based consortium of eleven leading offshore businesses and a university: Electricité De France, ADWEN offshore, SIEMENS Wind Power, RAMBOLL IMS, IBM Research, INDRA Sistemas, BACHMANN Monitoring, LAULAGUN Bearings, UPTIME Engineering and ZABALA Innovation Consulting and University of Strathclyde, UK. The project is led by IBERDROLA RENOVABLES ENERGÍA;

The main objective of ROMEO is to develop new advanced technological solutions to improve the current O&M strategy, consequently increasing the life span and reliability of the assets. A decrease in the number of failures leading to downtime and reduction in the maintenance contributes to the overall reduction in OPEX, which, in turn, lowers the LCoE of offshore wind energy

The project has span over 60 months. The project consists of 10 work Packages:

WP1 defines all the technical specifications & project requirements. A common framework ensures the good integration between WPs and the integration of end user requirements on the final concepts developed. Additionally, critical components (both for WT and support structures) in terms of life-cycle costs, are determined by failure modes effect and criticality analysis (FMECA).

WP2 provides WT Diagnosis/Prognosis solutions for a new design (physical). These focus on new mechanical drive trains and blade bearings. The developments of these WP include:

- Algorithms for increasing CMS capabilities of gearbox and main bearing WT diagnosis
- Blade bearing algorithms for rolling contact fatigue & structural health monitoring
- Algorithms to detect failure modes of permanent magnet generators, converter and transformers
- Scale model testing allowing extension to full scale components.

In WP3, both physical and statistical/machine learning models are developed, for the diagnosis and prognosis of critical failure modes on main WT components (main bearing, gearbox, blade bearing generator transformer). Datasets from the demonstration sites, from prototypes and from simulated synthetic environments are used for model training and validation. Modules are integrated within the cloud.

WP4 is focused on Structural Condition Monitoring (SHM). The feasibility of low-cost monitoring methods for predictive maintenance, risk based inspection and lifetime extension of WT structures and substructures when applied on an industrial scale using powerful FE (Finite Element) models and site-specific data are assessed. Benchmarking of hardware solutions and optimal sensor placement study, and 2 temporary monitoring campaigns for the foundation have been carried out. The studies conducted are to provide guidance on the implementation rationales for retrofitting already operating wind farms and for future wind farms.

WP5 provides a data framework of the information model for WF O&M strategy. It integrates the different data acquisition and processing elements and protocols that address the needs of the overall system in order to cover the requirements identified in WP3 and WP4. Multiple communication infrastructures, communication protocols and real time data processing have been demonstrated through this work package. The IoT cloud platform from WP5 has been considered. Interfaces validation tests on the 3 demonstrators' components. PCP (Power Curve Producible) and alert algorithm identification have been developed for edge computing capabilities (Node#1).

WP6 develops, deploys and demonstrates a fully operational Information Management Platform. The platform is centralised, web-based, fully integrated with central data acquisition and analytics ecosystem defined in WP5. Monitoring requirements for O&M platform are scoped, along with requirements for reporting and communication.

WP7 deals with all the pilot tests. Requirements are specified, connections for real time data aggregation and integration are tested, models are validated. Pilot validation covers the framework of the 3 critical and complementary Wind Farm use cases (Wikinger, East Anglia 1 and Teesside) operated by IBERDROLA and EDF using ADWEN and SIEMENS WTs.

WP8 carries out the impact assessment of the project. An integrated impact assessment numerical model that compares baseline cases with other design cases suggested through the project is developed. Various KPIs are measured, in terms of costs reliability and environmental impact.

This report gathers the main innovations developed throughout the lifecycle of the ROMEO project. In addition, some exploitable results identified by the partners are included. Table 1 provides a list of exploitable results.

Table 1: List of exploitable results of ROMEO project

Partner	Exploitable Result
ADWEN (developer)	Reliable product: 5MW WT with algorithms for monitoring
ADWEN (developer)	3rd generation 2. CMS integration for new developments (Main Bearing, Gearbox, Blade Bearing)
ADWEN (developer)	3th generation of CMS (above) may be implemented as retrofits on frozen WTs.
ADWEN (developer)	ML / Mathematical Condition monitoring development capability
ADWEN (developer)	Tailored Maintenance plan for equipment with 3th generation CM installed taking into account life degradation, P-F curves, based on RCM
SIEMENS GAMESA (developer)	Identification of WT components that have impact in OEE
SIEMENS GAMESA (developer)	3rd Generation of CMS integration for new developments (electrical train)
SIEMENS GAMESA (developer)	3rd Generation of CMS may be implement as retrofits on frozen WTs (electrical train)
RAMBOLL (developer)	RCM procedures for offshore wind industry
IBM (developer)	O&M Ecosystem demonstrator leveraging IoT Platform
UPTIME (developer)	Harvest O&M management platform
BACHMANN (developer)	Offline Diagnosis: New generation of CMS - including diagnosis support system and CM for Main Bearing and Gearbox
LAULAGUN (developer)	Sensorized bearing
INDRA (developer)	Interface to WFs data sources through BABEL using standard industrial protocols (ICCP, Modbus, OPC-UA, etc.)

INDRA (developer)	APIs and connectors to publish or subscribe to information on the real-time bus, iSPEED, for a particular product, system or library
INDRA (co-developer+IBM)	Rules and algorithms on top of the edge computing infrastructure already available in the smart nodes (Node#1).
BACHMANN (developer)	Offline Diagnosis: Support of RDS-PP designation system, a unique component reference for the service.
BACHMANN (developer)	Online Diagnosis: model based unbalance detection - sofware plugin / module
BACHMANN (developer)	Online Diagnosis: software for new hardware generation providing ISO RMS
IBM (developer)	Degradation detection and failure prediction models for WT components
EDF (developer)	Diagnosis and Prognosis algorithms for the electrical drive train – New wind turbines

3. Innovations

3.1. Failure Mode Effect and Criticality Analysis (FMECA)

Through WP1 of the project, a decision framework to prioritize offshore wind turbine monitoring was developed. In complex multi-component systems like wind turbines, it is very important prioritize systems for which condition monitoring would generate highest value and to understand the parameters that need to be monitored by a specific system from failure cause to failure mode.

There is a wide range of ISO standards on risk assessment as part of the ISO 31000 series[5] [6]. In the context of offshore wind turbines, both qualitative and qualitative methods are needed. FMEA (Failure Mode Effects Analysis) is a logical qualitative risk assessment process aiming at evaluating failure modes (FMs) of a process, procedure or system, their causes and effects. "Criticality Analysis" (CA) for failure modes classification, includes estimates of the likelihood and the severity of each failure mode. Therefore, when FMEA is combines with CA, then a semi-quantitative reliability method called Failure Mode Effects and Criticality Analysis (FMECA) is generated. It is commonly defined as 'a systematic process for identifying potential design and process failures before they occur, with the intent to eliminate them or minimise the risk associated with them' [7]. This enables the prioritisation of appropriate mitigation measures.

3.1.1. FMECA on major components

In the course of 12 workshops, that involved more than 40 technical experts of the ROMEO consortium partners, the major components risk profile of two wind turbine types and two different substructure concepts have been assessed. For this approach, the criticality of several failure scenarios of the wind turbine's main systems is assessed. Risks prioritization assesses:

- Which scenarios may occur
- How likely this is to happen

5 Purdy, Grant. "ISO 31000: 2009—setting a new standard for risk management." Risk Analysis: An International Journal 30.6 (2010): 881-886
6 ISO, I. "ISO 31010: 2009 Risk Management–Risk Assessment Techniques." CENELEC, Brussels (2010).
7 Juhaszova, Darina. "Failure Analysis in Development & Manufacture for Customer." Quality Innovation Prosperity 17.2 (2013): 89-102.

- What consequences will happen if the scenarios occur

The impact resulting from the use of a monitoring system can be evaluated. Criticality is hereby assessed under the consideration of failure consequences related to personal safety, the environment, asset availability, maintenance cost and the type of offshore intervention required.

A multi-step process to prioritize certain scenarios for further the further assessment is illustrated in Figure 1, as described in the standards [[8]][[9]][[10]][[11]].Criticality was calculated as a combination of failure probability and the consequences of the potential worst case end effect.

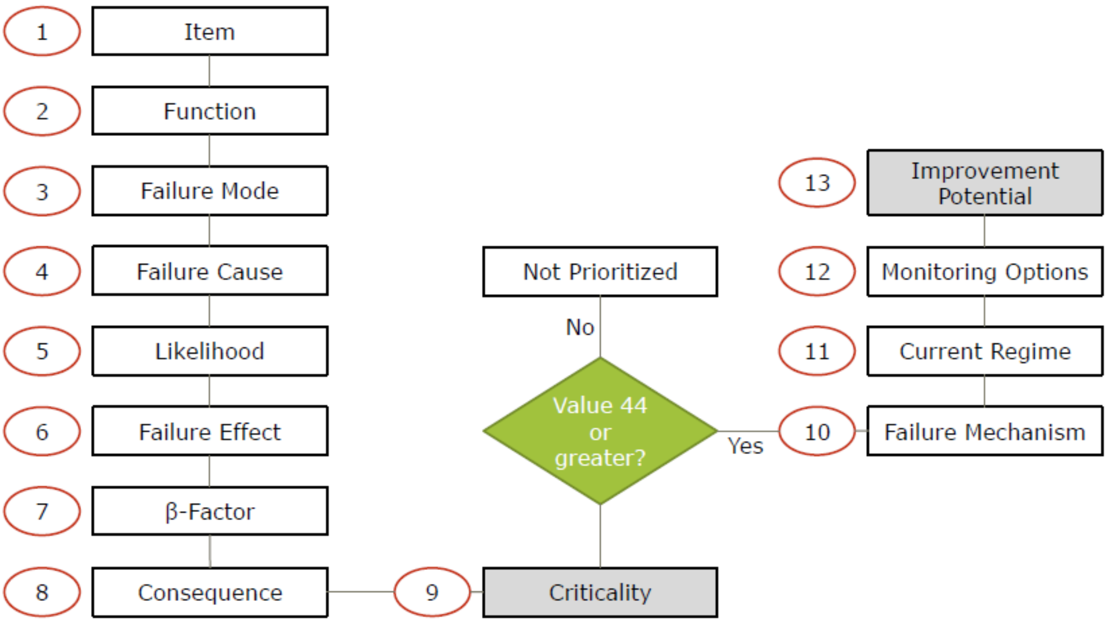


Figure 1: Process for FMECA

All failure modes with criticality values equal or greater than 44 have been prioritized. Figure 2 shows the proportion of criticality numbers per system in this criticality region.

[8] EN, C. "13306: Maintenance terminology." *European Committee for Standardization: Brussels, Belgium* (2001).
[9] International Organization for Standardization. *Petroleum, Petrochemical and Natural Gas Industries: Collection and Exchange of Reliability and Maintenance Data for Equipment*. ISO, 2006.
[10] DNV, RP. "A203 Qualification of New Technology." *Recommended Practice* (2011).
[11] Standard, Norsok. "Criticality analysis for maintenance purposes." *Z-008, Rev* 2 (2001).

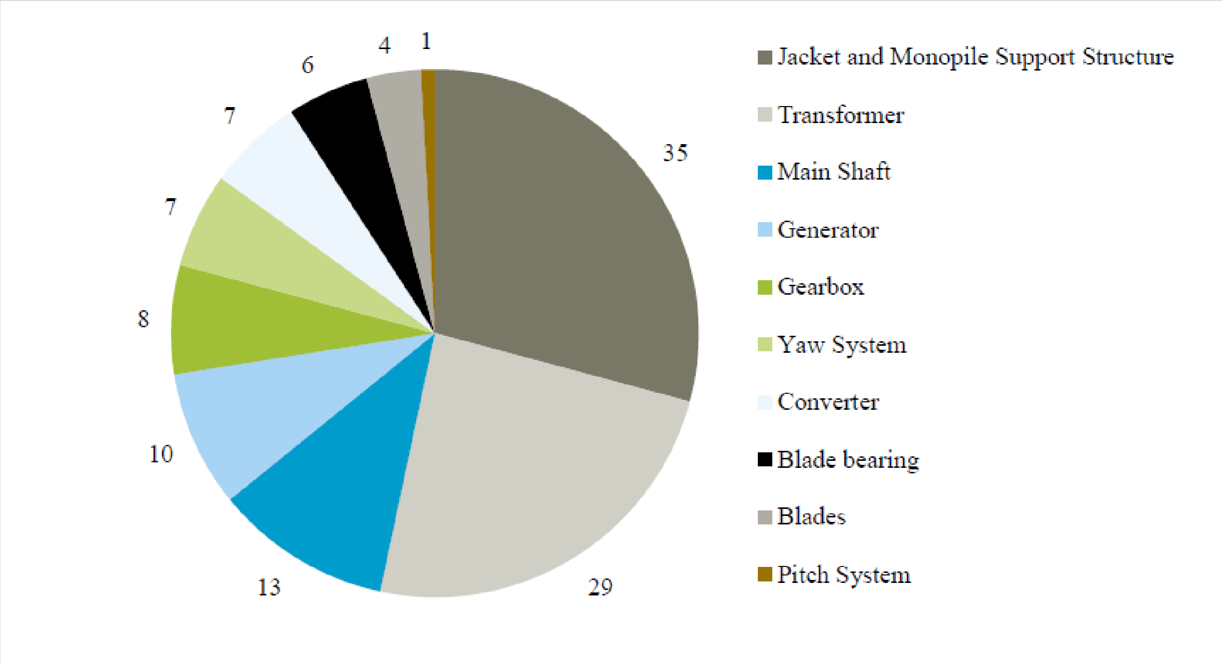


Figure 2: Number of prioritized failure modes for main systems

Offshore wind turbines are subject to maintenance strategies, with condition based maintenance being the currently most preferred methodology as it offers a balance between unplanned downtime and premature repairs/replacements. The Condition based strategies rely on information which is based on data gathered by continuous or intermitted, online or offline condition monitoring systems.

The risk assessment methodology described, provides the most important components that maintenance strategies should focus on. However, value is generated when status today is improved. The improvement potential is evaluated based on the expected benefits on cost reduction and downtime reduction. An important categorisation happens at this step; evaluation of improvement potential is carried out differently for the structures and turbine RNA (Rotor Nacelle Assembly) systems. This is because structures (here monopile and jacket substructures) structures are subject to an inspection and monitoring regime that shall ensure that structural integrity is kept throughout the intended lifetime of the asset. RNA systems (here blades, pitch system, yaw system, main shaft, gearbox, generator, transformer and converter) are, on the other hand, predominantly subject to regular maintenance campaigns which shall ensure that the components and systems are fit for their desired purpose. The evaluation for RNA components is performed using P-F intervals. The evaluation for substructures is performed based on benchmarking and on known physics in the in-between steps of the failure mechanisms. Particularly for the substructure structural components, the focus is on mechanisms that show time-dependant behaviour to allow for enough time for maintenance mobilization / failure prevention or mitigation prior to any undesired event to happen. Any evaluation that improves the status today is the focus of this project.

The above described evaluation is deemed to adequately reflect the prioritization procedure carried out for the ROMEO project. Any evaluation in the categories medium and high reflects an improvement of the status today. It shall be noted that not all critical failure modes have been assessed. Furthermore, it is important to that the design of maintenance strategies should be agile and flexible and this framework allows for inclusion and prioritisation of further monitoring systems.

3.1.2. FMECA for minor components

Each wind turbine major component is composed of multiple minor components with different failure modes which should also be addressed individually. Within ROMEO project, the FMECA methodology has also been applied to minor components of wind turbines.

The distribution of failure modes across subsystems is shown in Figure 3.

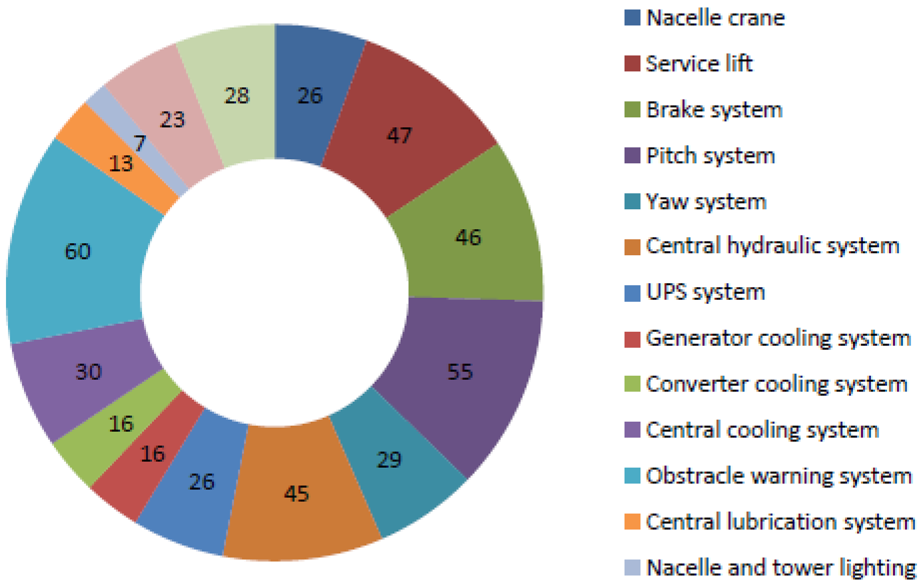


Figure 3: Distribution of failure modes for minor components

3.2. Diagnosis and Prognosis Solutions

On WP1, several failure modes were identified as part of the FMECA process. A fair distribution of failure modes and components was considered, in order to develop monitoring capabilities on different areas of expertise. All of them important for cost reduction. Having a wide set of components also allows to cover more failures that might develop during the project, giving direct feed to WP3 solutions.

However, in order to make the scenarios more certain, test benches were put in place in order to aid the development of the diagnosis solutions, so failure modes can be generated while the diagnosis system is being tailored.

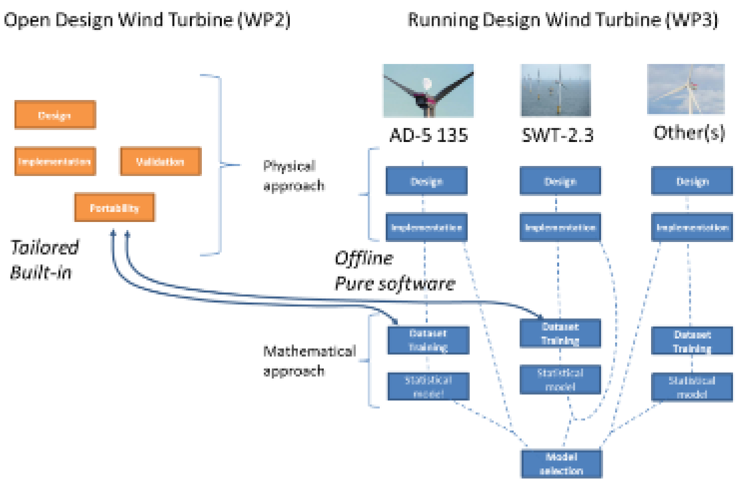


Figure 4. Very early development workflow approach.

ROMEO is a holistic, vertical integration of tools that focus on running machines. Due to this focus, it was deemed that also the most novel technologies are covered by the development effort, therefore WP2 allowed to provide an edge on the monitoring of the technologies that are yet to come.

3.2.1. Test bench experiments

3.2.1.1. State of the art

CMS implementation takes the approach of deploying a solution on top of an already built machine. A more integrated solution, in terms of design and adaption has been tried during this project.

At the same time, test benches would aid the following points:

- Taking the innovative approach of mimicking failure modes that have been selected for this study.
- Developing a monitoring system while algorithms are being developed;
    - Applying the general rule of thumb of investing time and resources at the beginning of a project is beneficial for the future life of the design and better operational data gathering from the prototype.
- Integrative view of ROMEO, taking into account that diagnosis systems form part of a bigger picture.
- Re-use of data: Preparation of Datasets for the potential feed of machine learning processes. When less data is available from the field, the test bench is a good complementary source.
- Collaboration: Allowing different partners to collaborate in the same scope (strengthening European collaboration).

All those points are commented in the following sub-sections.

3.2.1.2. Main shaft testing innovative approach

The objective of main shaft component inclusion was to provide advances to the state of the art of CMS: development, integration and adaptation to >8MW models. This innovative approach was taking into account bringing main shaft components close to end of life, therefore mimicking the failure.

3.2.1.2.1. On CMS development:

Ideally on the newest prototypes, CMS would be included in the Test Benching phase of a design.

This would allow to give a window of opportunity for the CMS to get adapted and tailored to this solution. This was an opportunity to get this exercise done on a more general framework of diagnosis and prognosis.

3.2.1.2.2. Integrative view

Integration with a more general system of decision making for diagnosis and prognosis. This would allow the operator to have daily infos on the needed changes that will arise on the fleet, on a more integrated, vertical way.

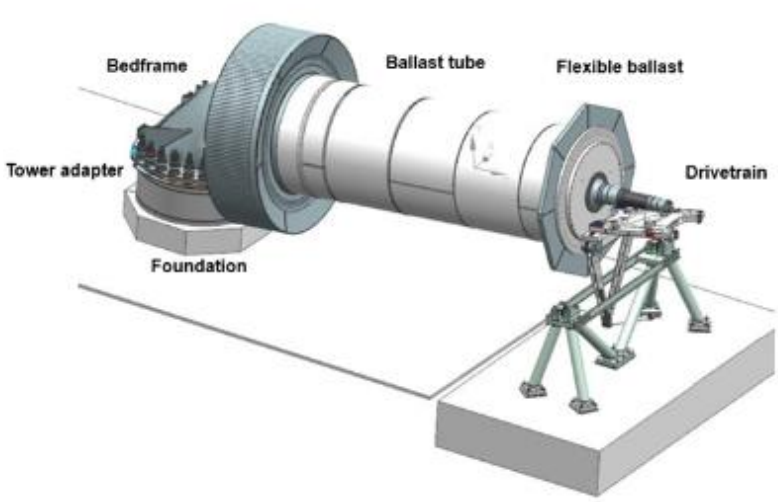


Figure 5. Main bearing test bench schematics.

3.2.1.2.3. Regarding re-use of data

SGRE and Bachmann studied thoroughly the case as an individual basis, and went for a deployment on a novel design. At the same time, the operating windfarms from ROMEO were providing enough quality data on all the fronts, so this was taken as an action for preparation for the future, and intercollaboration between partners. Apart from that, existing cases of synthetic data were already provided to WP3, before the testing occurred and in parallel with the start of data gathering on windfarm.

3.2.1.2.4. On partner collaboration

SGRE and Bachmann did a joint effort on locating a deployment of sensors for a newest direct drive turbine and perform a slot of testing during a test bench run-up.

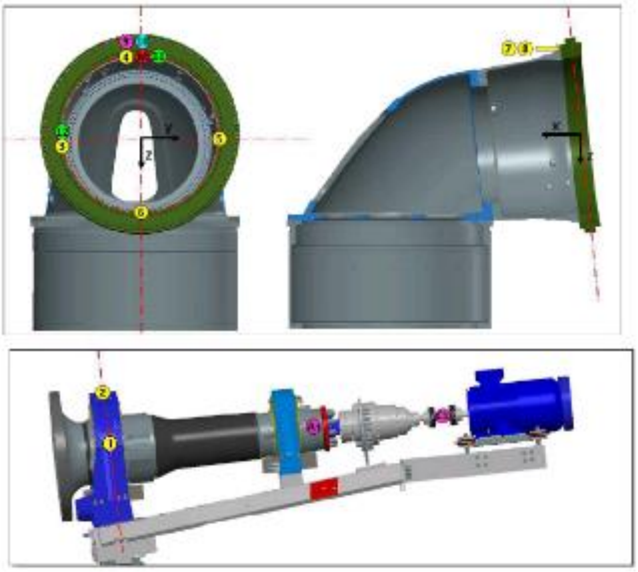


Figure 6. Mock-up on sensor colocation for the Bachmann CMS.

3.2.1.3. Blade bearing testing

The objective of blade bearing development of diagnosis product was to depart and make feasible a development of CMS for blade bearings for the first time. The objective machines were >8MW models which could take the whole benefit of the advances. This is important because, at the same time that blade bearings have low failure rates, their failures require critical action with a special vessel, complex replacements and some of the failure modes are worthy to mitigate due to structural considerations. Therefore, even if the failure rate is low, the criticality and the opportunity cost of developing a CMS for the first time would bring a substantial benefit to the case.

Similar to the main bearing, this innovative approach has taken into account bringing main bearings close to end of life, therefore mimicking the failure.

Figure 7. Blade bearing test bench.

3.2.1.3.1. On CMS Development:

A specific test bench for blade bearings was set (see Figure 7).

In this test bench, a box with the capability of monitoring was installed (see Figure 8)

Figure 8. Windbox instrumentation CMS.

Both algorithms were developed, implemented and validated:

- Rolling contact fatigue
- Structural integrity

In parallel, for SGRE purposes and joint investigations, a number of algorithms and a test in field was deployed in order to check if some of the ideas created within ROMEO project were feasible to implement in newer designs. This work has been documented in D2.4.

3.2.1.3.2. Integrative view

Advances on the integrative view of ROMEO came by using common notation for sensors and the usage of diverse technologies within the project. (Electrical / Hydraulic)

3.2.1.3.3. Regarding re-use of data

One dataset resulting from the testbench generation of failure was developed. This was parsed for WP3 anomaly detection consideration, as blade bearing failures are very rare to occur and no samples were found during the duration of the project.

3.2.1.3.4. On partner collaboration

SGRE and Laulagun shared knowledge sessions and explanations on the respective algorithms deployed, as well as the effectiveness of each approach. Also, the data that WP3 could inherit was done in consensus as an alternative to not having field data (since blade bearing occurrences are more rare).

3.2.1.4. Electrical testing innovative approach

Different types of varying speed wind turbine generators have been developed: doubly fed generators, induction generators with full power converters, direct drive synchronous generators with full power converters, mid speed synchronous generators with full power electronics. Among these different types, most common technologies presently installed in offshore wind farms are direct drive or mid speed synchronous generators with full power converters, that enables to relieve stresses within the gearbox (mid speed) or to get rid of the gearbox itself (direct drive) and of the associated O&M costs.

The electrical components of the wind turbines are mainly: the generator, the converters and their DC bus capacitors, the transformer, the switchgears. Each of these components are subject to specific failure modes related to different physical mechanisms. For instance, the degradation of insulation of windings or connection cables can be related to: overheating and chemical degradation of the insulation, possibly influenced by hotspots, overload; vibrations and associated mechanical abrasion, notably in slot sections and end windings; partial discharges associated to cavities or impurities, and possibly influenced by the harmonic content; Overvoltages, electrical stress surges due to operations.

Quite often the electrical failures seem to appear suddenly, this is either due to the apparent brevity of the physical mechanisms of the degradation pattern, and/or due to the lack of adequate observability.

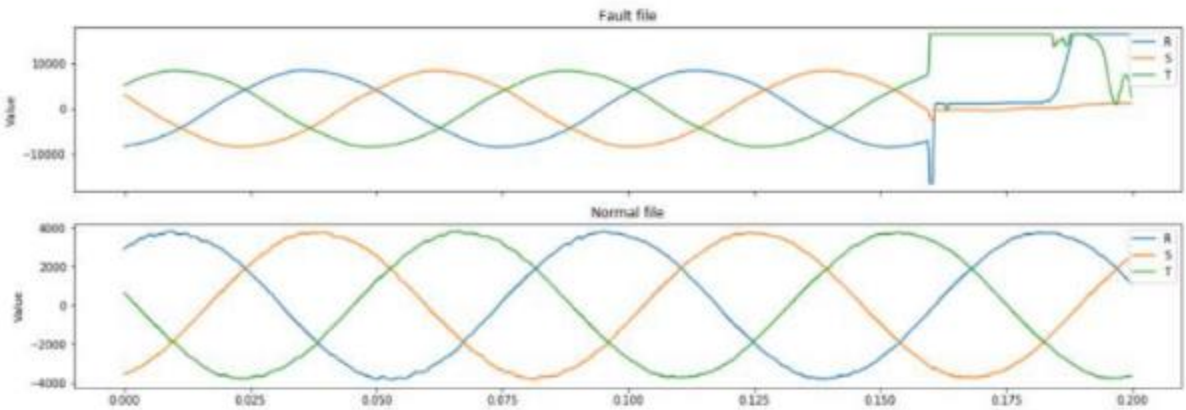


Figure 9. Example of a Converter failure, manifested suddenly when the failure was tracked back with the aid high frequency data, but difficult to catch on the fly as this would need a manual process.

Most available operational data on conventional wind turbines correspond to 10-minute average. Very few operational data are available to characterize electrical failure modes, helping to develop and testing diagnosis and prognosis algorithms. In addition, electrical tests of electrical failure modes on full scale generators, despite not impossible, are generally not done, due to their complexity, and due to reticence to perform tests possibly destructive at these power levels.

3.2.1.4.1. Regarding re-use of data and partner collaboration

Regarding both re-use of data and partner collaboration, the electrical subpart of ROMEO has taken a particular approach in order to investigate electrical failure modes:

- Full-scale data from prototypes or operational turbines, with generally lower sensor set up.
    - A challenge to overcome with this approach was to get faulty data with high frequency.
    - Notably full-scale data have been obtained with 8 years of SCADA data on EDF Group Teesside windfarm.
    - Siemens Gamesa has listed subsets of full-scale data compatible with the electrical approach. This full-scale data would enable investigating and scaling up the diagnosis and prognosis algorithms in the long term.

- EDF R&D 60kW Small-scale test bench data with possibility to represent generator faults in a well controlled environment. EDF R&D has developed a small-scale test bench dedicated to study electrical machines similar to generators of onshore and offshore wind farms. This bench test is located at EDF Lab Paris-Saclay. Commissioned in 2020 for "healthy" operation, it has been used between 2020 and 2022 for "healthy" and "unhealthy" operation (representative of incipient faults). The bench test is reversible, it is composed of two electrical machines (one permanent magnet synchronous machine and one doubly fed induction machine), that can work alternatively in generator or motor mode at variable speed. The designs of these machines are chosen with an electrical and magnetic architecture similar to the generator of wind turbines. The motor reproduces the rotation of the wind turbine's rotor blades, via torque and speed control. The generator and power electronics reproduce the wind turbine's generator, the converters, transformer and the connection to the network. Figure 10 presents a view of the laboratory and a focus on the doubly fed, the synchronous generators and the one stage gearbox, and a one-line diagram:

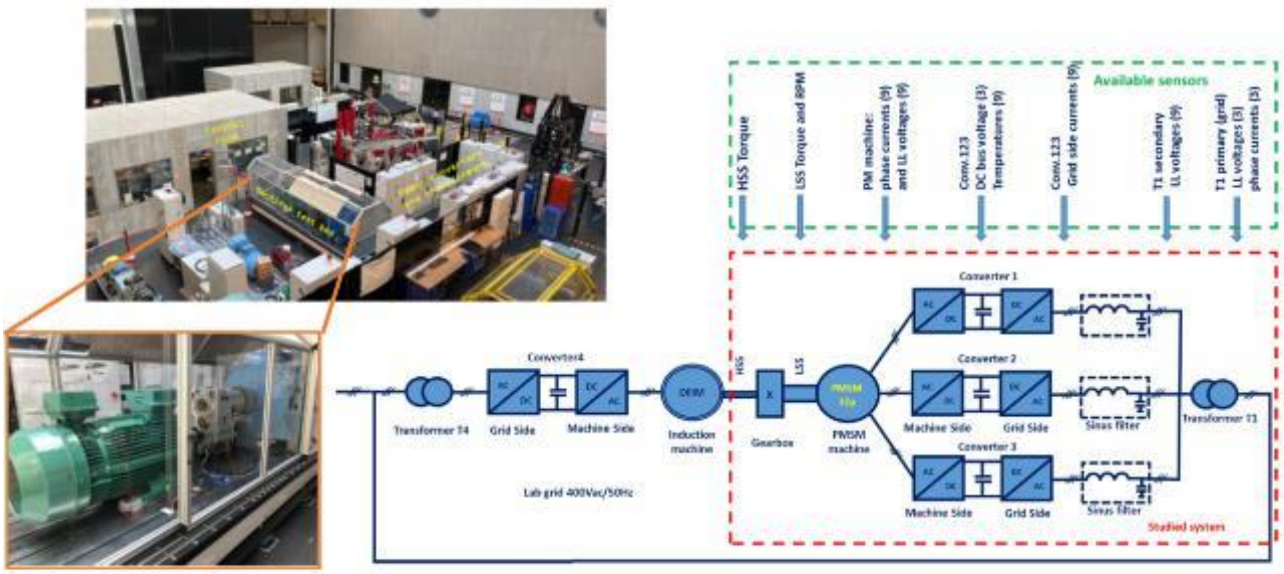


Figure 10: 60 kW – EDF R&D Small scale bench test

The test bench is constituted of: a clamping plate for electrical machines, with housing; two electrical machines: a motor and a generator; a gearbox; mechanical and electrical sensors; four cabinets of power electronics developed by EDF R&D; a control system developed by EDF R&D. With this test bench, in the framework of ROMEO European project, "healthy' operation test cases have been run along with "unhealthy" operation test cases (limited to DC bus degradation, phase-ground, phase-phase and interturn short-circuits within the dedicated synchronous generator, despite extended capabilities to address other topics).

Diagnosis and prognosis algorithms have been developed and evaluated trying to benefit as much as possible from the small-scale and full-scale data available, and accounting for a methodology suitable to account for the various machine's scales.

3.2.1.4.2. On diagnosis and prognosis developments around specific components

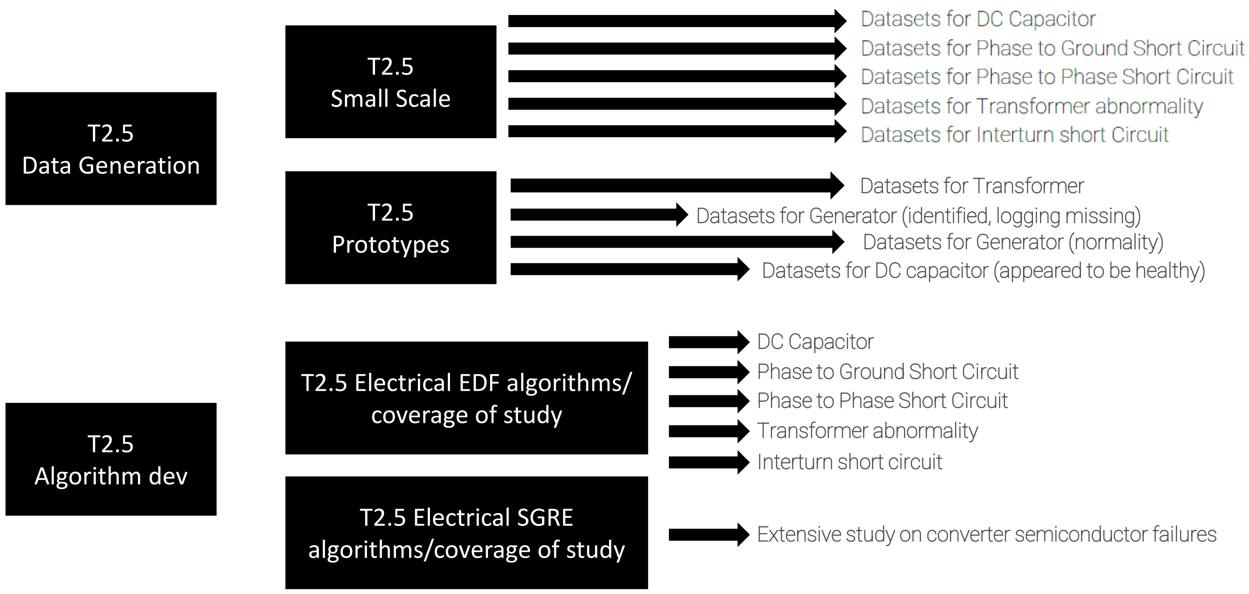


Figure 11. Summary of Task 2.5 algorithm work and data generation.

The electrical components addressed are:

- The transformer: EDF has developed and evaluated an algorithm associated to the transformer. Transformers in wind turbines have particularities related to the environment in which they are placed with space and environmental constraints. Generally, in wind turbines, it transforms a low voltage (for instance 690 V) on the generator side into a high voltage (for instance 33 kV) on the grid side. These very compact transformers are often cooled by a heat transfer fluid.
  Many aspects must be taken into account for the operation of transformers: oil quality (for submerged transformers), quality of cooling, operating conditions, aging of internal circuits (windings, insulation). The transformer is therefore inseparable from ancillary components which must also be kept in perfect working order (cooling system, air dryer).
  The transformer must therefore be able to withstand without damage both the vagaries of the electrical network: over-voltages, short circuits, inrush currents and overloads and other constraints related to its environment. The algorithm developed is based on several indicators accounting for the operational conditions, the refrigeration system, the windings, the oil quality, the air quality and the oil level. It has been successfully evaluated with operating transformer data.
- The generator: EDF has developed algorithms for phase-ground short-circuits, phase-phase short circuits and interturn short-circuits. A phase ground short-circuit is an unexpected current from an active phase to ground. A phase-phase short-circuit is an unexpected current from an active phase to another. Interturn short-circuits are unexpected current between internal turns with the generator. These failure modes can be associated to degradation of insulation of windings or connection cable, mechanical breaks related to electrodynamic forces due to short-circuit, degradation of bushings. The goal of the algorithms developed is to detect early enough the incipient fault so as to adopt adequate O&M actions, notably preventing the situation from escalating. The evaluation of the algorithms developed within ROMEO for the generator has been positive with the small-scale data. As future work, implementation and evaluation for on-field full-scale operating wind turbine are considered.

- DC bus capacitor: EDF has developed an algorithm to detect degradation of the DC bus capacitors of wind turbines, that can be related to aging of the material. A positive evaluation of this algorithm has been obtained with data from the small-scale bench test in normal & abnormal operation. At this date, full scale data have been considered lacking however from experienced failures.
- Converter: SGRE has developed a number of methodologies and approaches which could lead to prevent failures on converters.
    - Failures of converters involve IGBT failures which can cause downtime of the converter and degradation.
    - Approaches taken are:
        - Use of SCADA data and variables;
        - Use of high frequency data;
        - Possible improvement: Development of a dedicated data acquisition system.
    - Failure isolation is possible to be done with both SCADA / High frequency data;
    - High frequency methods for converter failure detection are considered the feasible way to monitor an earlier defect on semiconductor components (See D2.4)

3.2.1.4.3. On converter high frequency methods:

Upon inspection of the converter semiconductor failure signals, it was discovered that many of them had a sudden change of slope when the signal was close to zero, and this behaviour was almost never seen under normal operation.

Example: In the following figure, on the left, current signal (three phases) for failure signal (up) and for normal signal (down). On the right, the comparison between the first derivatives of the current signal of phase R (failure (up) and normal (down)).

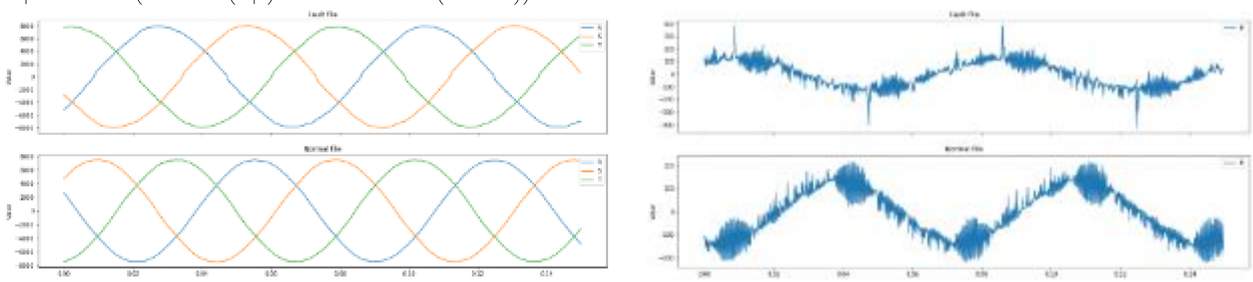


Figure 12. Example 1 of the approach 11 (Very High Frequency data) "Detect blow-ups using spikes in the derivative of the current signal"

3.2.1.4.4. Integrative view

Regarding the integrative approach of this line of investigation and development, both partners SGRE and EDF participated in the proper selection of a machine that would represent better offshore operation.

The amount of sensors present in the testbench was cross checked between the datasets that were submitted/operative within WP3 and EDF's bench deployment.

3.2.2. The importance of CMS systems

3.2.2.1. Unbalance algorithm

Given the current focus on trying to reduce the Levelized Cost of Energy (LCOE) and approaching or exceeding the wind turbines design life, individual component wear caused by mechanical interaction has taken the limelight for the industry. One common culprit of mechanical vibrations for turbines is rotor unbalance. This unbalance, which originates at the blades, transfers through the entire drivetrain, shortening the service life of the mechanical components, as well as the turbine structure and even the foundation. The resulting component failures translate to long downtimes and excessive costs to owners.

Traditionally, unbalance measurements require technicians on site. They must equip turbine blades with trial weights and take several vibration readings in order to calculate the unbalance. This process presents safety risks and leads to production loss. Moreover, unbalance calculations, as performed today, are generally only triggered by gross deviations from the norm which cause technicians to positively identify the need for balancing.

Bachmann implemented a model-based approach for rotor unbalance calculation, which can reduce safety risks and production loss, as well as provide a clear trend with greater sensitivity for balancing. This model-based approach can estimate the mass unbalance during normal turbine operation without the need of applying test weights for the unbalance estimation. As part of an online condition monitoring system, rotor unbalance calculation can enable owners to incorporate rotor balancing into their predictive maintenance strategy. Corrective actions can be taken ahead of time, reducing wear on the drivetrain, and leading to increased component life.

The validation within Wikinger was based on a ranking provided by Bachmann for the most affected turbines. Figure 13 shows one turbine with a very high aerodynamic imbalance. This aerodynamic imbalance was compensated. SGRE were able to correct the pitch angle remotely by adding an offset to the control configuration and thus compensating the aerodynamic imbalance.

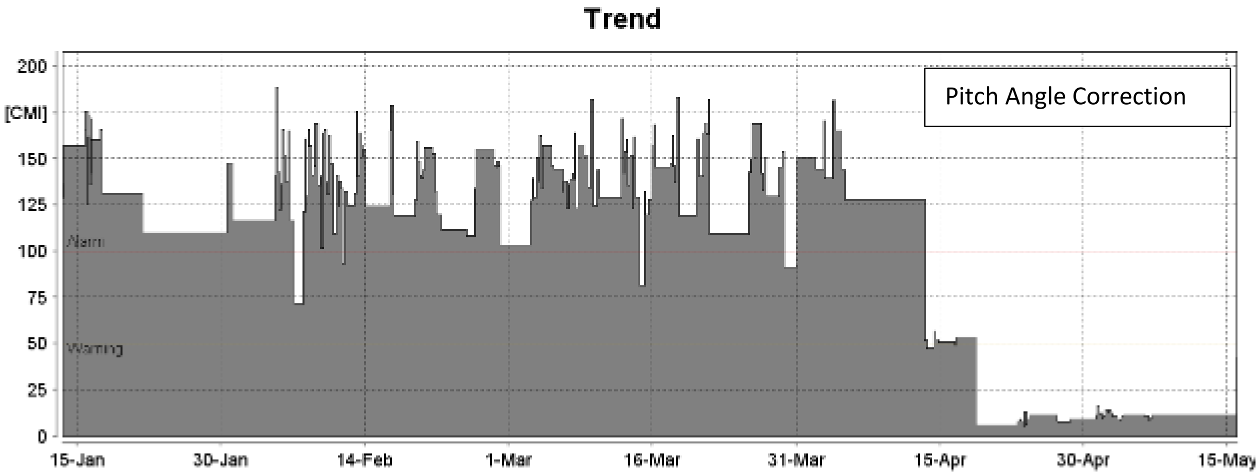


Figure 13: Aerodynamic unbalance example from Wikinger (CMI – normalised condition monitoring index, 100 equals alarm threshold)

3.2.2.2. FMSA and Damage classification

Modern O&M concepts include the use of software platforms, which gather, link and visualize data from various sources. Data streams include -among others- met-ocean data, component availability or current vessel cost. Condition monitoring data plays a key role supporting the O&M service to plan and optimize their actions. In condition monitoring, vibration data can be combined with other information from the turbine control system, like temperatures, particle counts, pitch angle, etc.

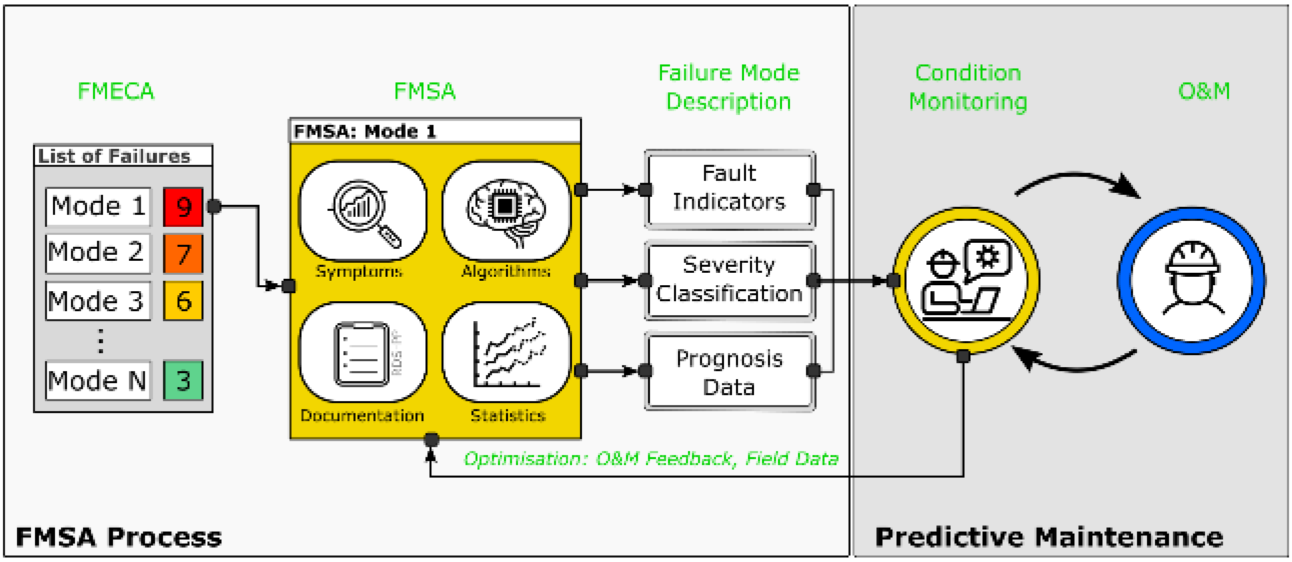


Figure 14: Overview of the analysis

Within the ROMEO project a methodological approach to the failure mode symptom analysis (FMSA) was developed and implemented. It describes the process of deriving diagnostic indicators based on sensory input. Based on an FMECA, critical components are identified and further analyzed within the FMSA. In practice, one failure mode is described by a list of indicators. Using multiple indicators for one failure mode is advantageous, as they provide detailed insights in the component's condition. Although one indicator may be enough to detect a particular failure; the combination of several indicators enables the severity classification of this failure, (see Figure 15).

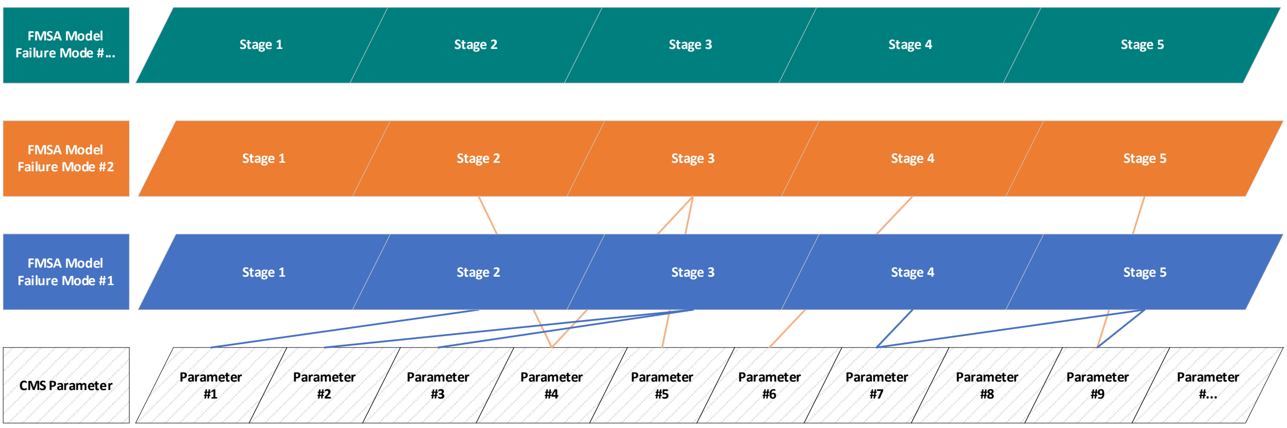


Figure 15: FMSA assigns diagnostic symptoms to failure mode & severity

This section presents a FMSA for a bearing component. For this exemplary application, the set of indicators shall:

a. detect raceway damages of a particular bearing type from a very early phase.
b. yield a high detection rate.
c. exclude (minimize) the chance of a false positives.
d. enable a severity classification.
e. enable prognostics / point to failure estimation.
f. work for typical operational states of the turbine.

While (a) to (c) are conventional condition monitoring requirements, (d) and (e) introduce novel diagnostic challenges to the FMSA process. Following the VDI 3832, 5 stages for damage classification are applied.

Figure 16 shows multiple diagnostic indicators and how they can be used for monitoring the transition from a particular phase to another. The software identifies the change of the monitored parameters from normal behavior (green) to a more severe state (red).

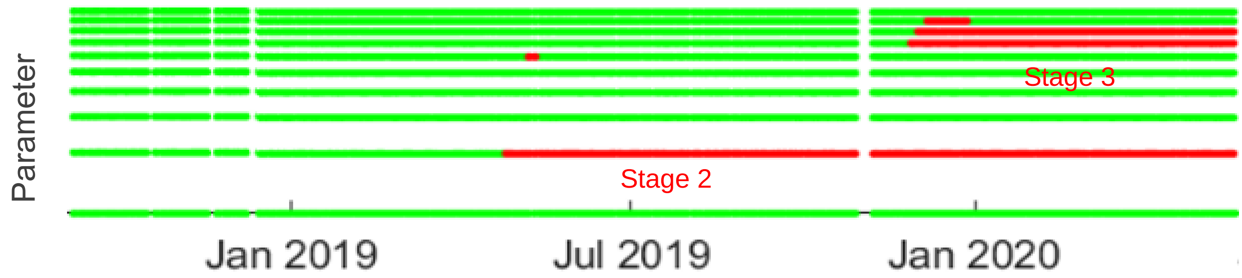


Figure 16: Parameter change and correlation with the severity stages

As shown in Figure 15, these symptoms than can be assigned to the failure mode and severity. The advantage of the FMSA is the automated combination of the diagnostic symptoms, which can be supported by machine learning. In addition to the identification of the failure mode, the severity and lead time to failure can be estimated.

The method has been applied on two offshore wind farms within the project. The selected failure indicators yielded for a detection rate of 100% with zero occurrences of a false positive. After repair and replacement services, the O&M team analyzed the condition of every damaged component. In all cases the CMS estimated the damage class correctly. Moreover, both the O&M and monitoring teams ranked the damage cases according to their severity have a 100% match.

3.2.2.3. Software for new hardware generation providing ISO RMS

3.2.2.3.1. Drive train

For many industry branches standards for measurement and evaluation of machine vibration have been available for many years. For wind turbines guidelines (Germany , VDI 3834-1 and 3834-2) and standards (ISO 10816-21) have been published or are under development (ISO 20816-21).

These standards cover the measurement and evaluation of the mechanical vibration of wind turbines and their components. The ISO 20816-21, which is currently under development, will cover horizontal axis wind turbines with a gearbox and without a gearbox (direct drive).

Modern condition monitoring modules, like Bachmann's AIC214, provide characteristic quantities (R.M.S. values) in real time 24/7. The R.M.S values can be accessed over various field bus protocols and integrated into the turbine's SCADA and control system (Figure 17). The turbine control can react immediately in order to reduce loads and to prevent critical conditions.

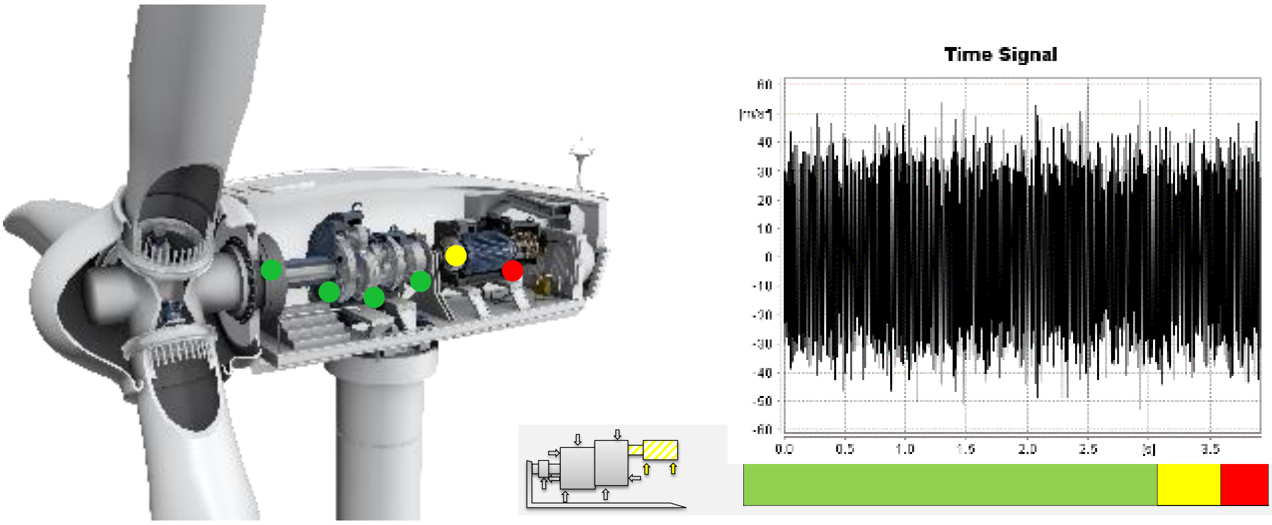


Figure 17: SCADA visualization (left) based on ISO R.M.S level (right)

The SGRE main bearing test bench in Brande was used for the evaluation of the hardware and software. Figure 18 shows the results and correlation between the R.M.S, torque, and rotor speed. The characteristic quantities provide a very useful real time information about the vibration and of the drive train, which can be used to avoid critical operation conditions or as a first indicator for required maintenance actions.

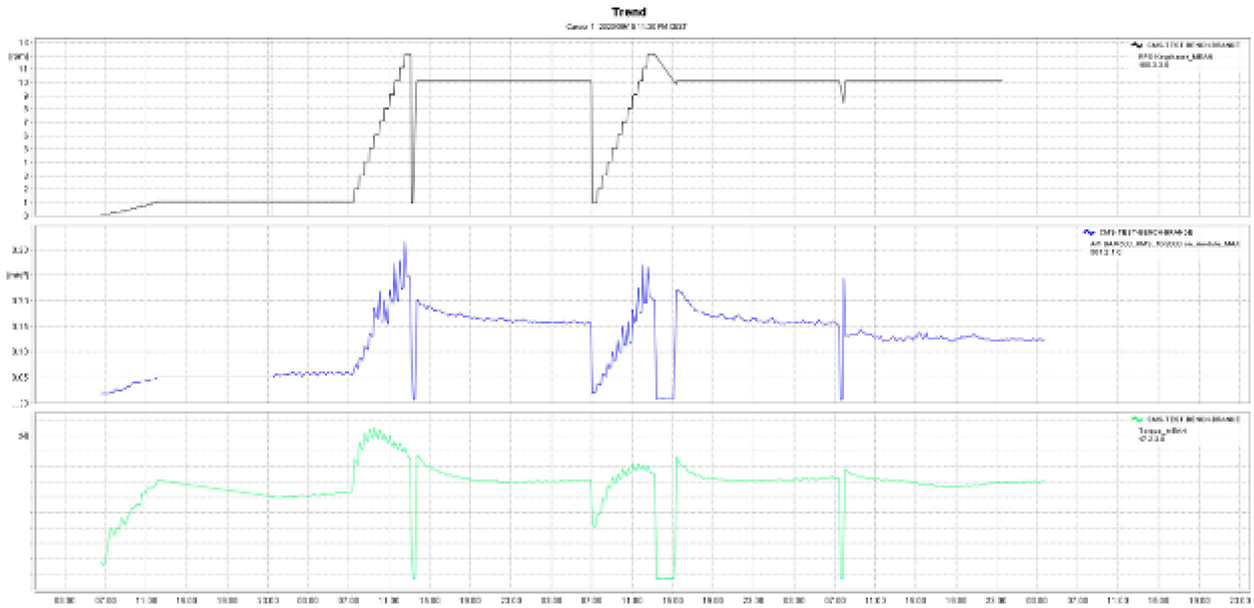


Figure 18: Results from the test bench

3.2.2.3.2. Outlook, application for Structural Health Monitoring

In addition to drive train monitoring, load reduction and machine protection play an important role in Structural Health Monitoring (SHM) applications. The guidelines VDI 3834-1, VDI 3834-2, VDI 5451 as well as the ISO 10816-21 provide basic characteristic quantities. The example in Figure 19 shows the daily maximum RMS. level measured at the tower. More than 2 months of lifetime have been consumed by only 2 events, which can be seen in the comparison of the quarterly rain flow counts (Figure 20).

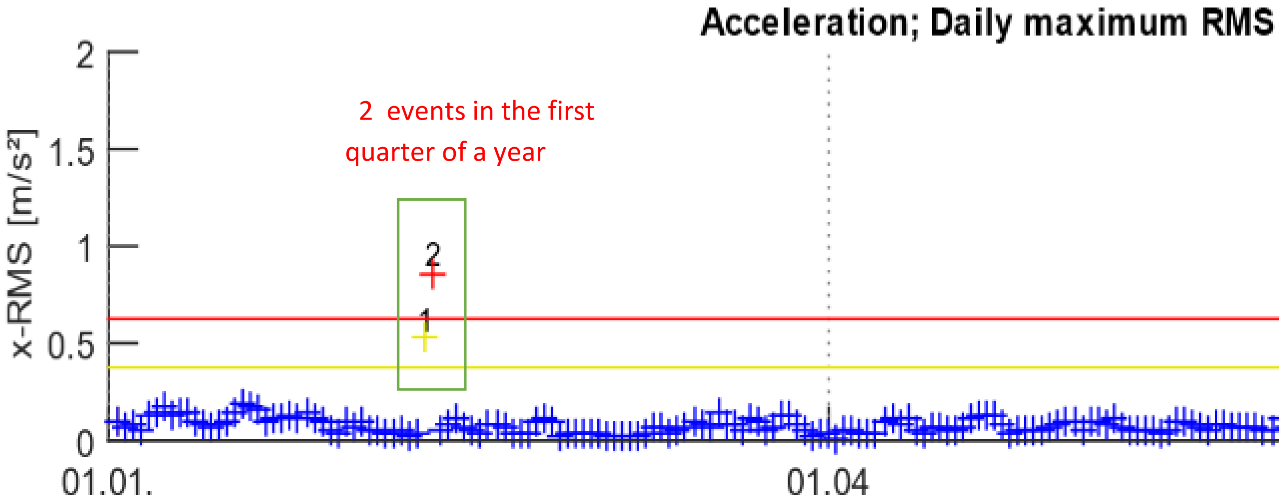


Figure 19: Events with high vibration level and load in the 1st quarter

Further data from our current SHM applications reveal, that single high load events can yield for a loss of up to 10 months of structural lifetime. A Holistic Monitoring Concept for the whole wind turbine and data exchange with the turbine control can be used to reduce these loads and thus avoid critical operational conditions for the WTG.

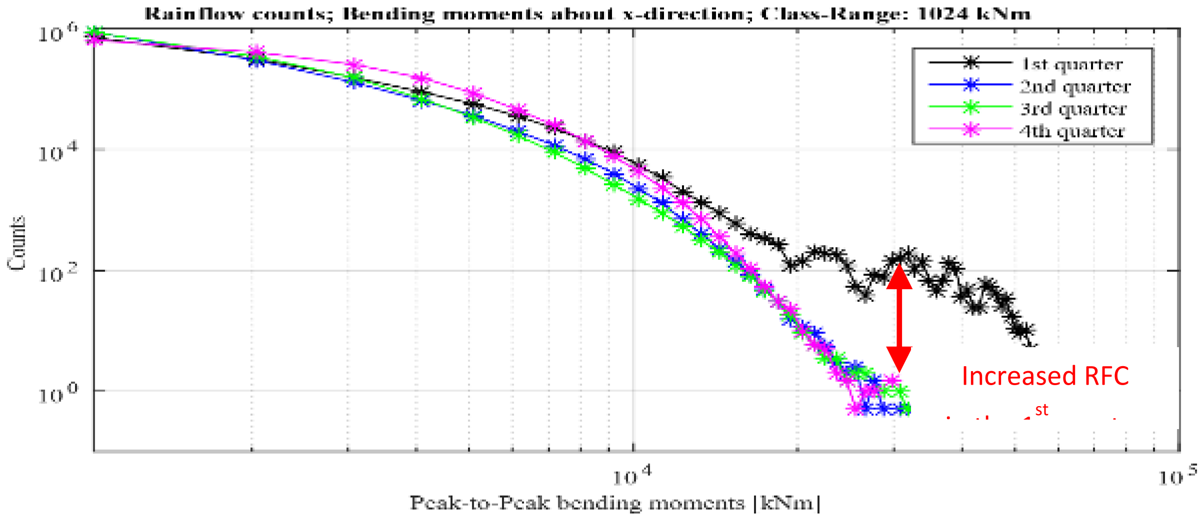


Figure 20: Increased RFC in the 1st quarter as a result of only 2 events

3.2.2.4. Blade bearing

The importance of being able to detect a failure mode is crucial, especially for those offshore wind turbines where the access is very limited. For this purpose, CMS systems are becoming very important and Laulagun has been working in two test within Romeo Project to develop a technology valid for the blade bearings.

The objective of both tests is to design and validate a solution for the most critical failure modes in blade bearings and develop a method for the diagnosis and prognosis of these failure modes. For this, 8MW Windbox Test bench have been used, where Laulagun CMS has also been tested and integrated for the development of this new capabilities.

In the following diagram, a description of how the methodology works for the selected failure mode can be seen in Figure 21¡Error! No se encuentra el origen de la referencia..

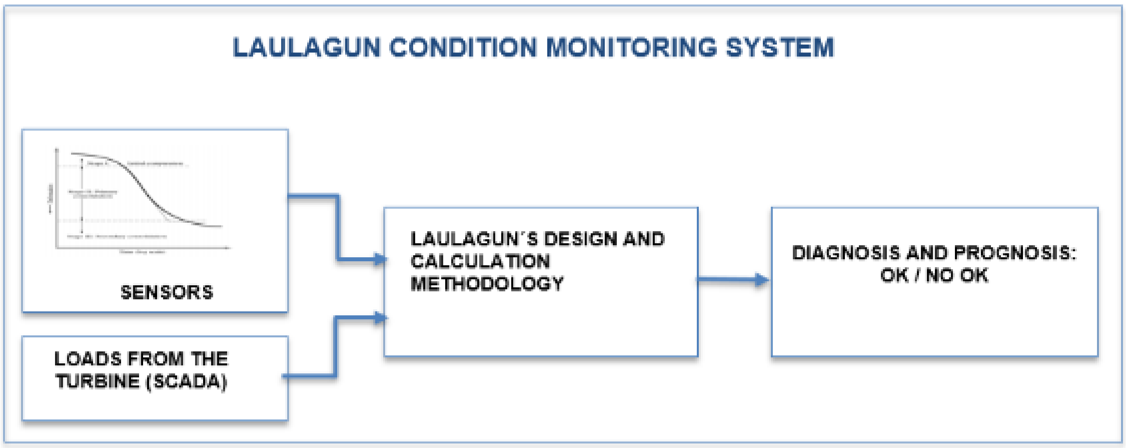


Figure 21: Laulagun Blade Bearing CMS

As it can be seen in the diagram, the methodology is fed by the information provided from the sensors and data monitored by the turbine (commonly known as SCADA). For the selected type of failure mode, the most common sensors are strain gauges and displacement sensors. Depending on the design, also fiber optic sensors can be used as most complete alternative to the strain gauges to measure temperature and vibrations apart from the strain. That would require to upgrade the CMS, adapting the acquisition system or even integrating an extra interrogator to the whole system. Apart from the selection of the sensors, what is also crucial is the positioning and the instrumentation of them in the blade bearing, where criteria rules that the most stressed areas should be sensor equipped. Depending on the characteristics and design of the bearing, Laulagun´s methodology would calculate the damage that is being generated all the time, and this would be accumulated to estimate how much time the bearing will work or will remain working before any possible failure mode will appear.

The methodology will specifically focus on obtaining the loads in the hoop area where the gauges are placed (blade root fixed / blade root pitching). In addition, if the calculation in the other hoop area is needed, it would be necessary to measure the pitch angle. Normally, to get this pitch angle parameter it is possible to work directly with the SCADA and correlate data using this system.

After understanding the loads provided from the SCADA, together with the data from the sensors, the stresses in the points of the bearing that have been considered as more important for their monitoring will be known. At the same time, these calculated stresses are valid to estimate the damage to fatigue that the bearing is suffering at each moment.

To finish off, as it has been stated before, the accumulated damage would be calculated and this will enable to estimate the remaining life thereof with respect to a predefined threshold of maximum damage allowed (which would indicate a possible crack initiation).

All this knowledge will be integrated in a Condition Monitoring System that will have external communication capabilities. This system will give information about the status of the blade bearings and will be configurable to any kind of reception system, depending on the OEM.

3.2.3. Applicability to other wind turbine types and arrangements

3.2.3.1. Integration of the CMS as part of the drive train

3.2.3.2. Diagnosis and Prognosis algorithms for the electrical drive train – New wind turbines

- New wind turbines in offshore wind have various designs, that the algorithms for diagnosis and prognosis have to accommodate as much as possible natively. In ROMEO, the wind turbine types taken into account are:
  - Either a direct drive type: a multipole generator enables to get a low physical rotational speed for a higher electrical frequency at the stator voltage $\mathbf{f_{elec}} = \frac{\mathbf{N_{poles}} * \boldsymbol{\Omega}_{\mathbf{rot}}}{\mathbf{4\pi}}$. The use of this larger and heavier generator enables to spare the use of a gearbox and associated impact on O&M. As an example, a 7.5 rpm speed with 200 poles will enable a 12.5 Hz frequency. The generator is connected to the grid through a back to back converter.
  - Either a mid-speed synchronous generator combined with a one stage gearbox. This configuration enables to use a more compact synchronous generator than the direct

drive, and partly alleviates drawbacks of the gearbox with a simpler and sturdier design. The generator is connected to the grid through a back to back converter.

These synchronous generators can have several three phases circuits, with or without phase shifts between the circuits.

Wind turbine power electronic converter systems are generally composed of:

- A machine side Voltage Source Converter: assembly of IGBTs. The architecture can be a one stage (2 voltage levels 0 & Vc being the dc bus voltage), or a multistage (for a 2-stages, 3 voltage levels, 0, ½ Vc, Vc)
- A DC bus: the capacitor value is chosen to limit the DC bus voltage variations.
- A grid side Voltage Source Converter like the machine side voltage source converter
- A filter on the grid side to meet required power quality. The size of the filter depends on the architecture
- A control system unit with associated measurements, for control purpose (Phase Lock Loop, Pulse Width Modulation generation, etc) and for protection purpose (temperature measurements, current and voltage measurements)
- A charging circuit for starts
- Possibly a Fault Ride Through apparatus connected to DC bus to evacuate energy during grid faults

To some extent, modular designs can be adapted with several power electronic converter systems in parallel, or on different generator's 3-phases circuits. The converter system is prone to IGBT's failure, hardly predictable, and is in 2021, a significant provider of maintenance actions and unavailability. A significant effort is done in the development of fault resilient architectures for converters. Redundancy is a costly solution, however the modularity enables operation in degraded mode.

There are various possibilities associated to the grounding system, that will have their importance for the purpose of diagnosis & prognosis. The choice made in the present case is to consider an electrical drive train configuration with a grounding impedance on the grid side LV voltage, at the neutral point of the filter. The use of a different configuration will require an adaptation of the diagnosis algorithm.

- The developments made within ROMEO have taken as much as possible into account these possible variations of electrical drive trains, with however adaptations being possibly required depending on the design specificities. Concerning the portability of the algorithms developed, it can be noted:
  - Hardware changes for measurements: no hardware change is identified as mandatory for improvement of the detection as, with the diagnosis method presented, the measured voltages and currents required are available from the wind turbine controller. It however assumes that:
    - Either the diagnosis algorithm can be integrated within the wind turbine controller.
    - Either a on-event transmission of data is set in place between the wind turbine controller and a remote processing unit.
  - Adaptation to different grounding connections: the algorithms developed and evaluated for phase-ground short-circuits correspond to a grounding connection on the grid side of the generator. An adaptation of the algorithms for the other grounding topologies is required but can be straightforwardly performed.
  - Adaptation to other design differences: the differences of wind turbine design constrain the portability of diagnosis/prognosis algorithms for various algorithms. Among these differences, one can note: the converters configuration (N-level converters, parallel

converters); the windings & phases arrangements of the generator (for instance single/multiple stars, parallel or phased), the grounding scheme. The algorithms defined, implemented, and evaluated do correspond to a specific configuration. Nevertheless, the methodology/algorithms can be straightforwardly adapted to other configurations.

- Though providing satisfactory results, further improvements of the algorithms developed are possible, notably with additional work on classification methods and associated thresholds, or on complementary decision making algorithms.

3.3. Failure Mode Models for Wind Turbine Components

3.3.1. Physical Models

The objectives regarding ROMEO shall be well aligned with the development of failure mode detectors and the integration of those into a more holistic system.

One of the objectives of the ROMEO project is read as:

- **OO2: Develop the physical approach for detecting and programming failures with a few number of robust sensors.**
  - Abnormality datasets generated for 2 out of 3 failure modes (WP2).
  - Validation process of algorithms being conducted for electrical drive train with new abnormality

The development of physical approach methods with robust sensorics has been dealt within D3.1 and D2.1.

Each of the technologies/machines that are running and were included inside ROMEO project as part of the scope have received more or less focus regarding failure mode detector development (see D3.1 within Task 3.1):

- EDF Teesside wind farm: EDF Teesside offshore wind farm is composed of 27 turbines of 2.3 MW, that are squirrel cage induction generator with full power electronics. The windfarm is operating since 2013, enabling EDF and ROMEO project to rely on a significant amount of operational data from the SCADA system and from the CMS system, limited to the existing monitoring system capabilities. For this operational wind farm, in the scope of ROMEO project, diagnosis and prognosis algorithms have been developed, implemented and evaluated on a monthly basis:
  - Blade/pitch system: the goal of the diagnosis & prognosis algorithm implemented is to detect failures associated to the blade or pitch system, notably the blade bearing. Due to identified limitations of the measurement system available at Teesside, it was unfortunately not possible to account for the physical degradation modes as thoroughly as expected. The physical algorithm developed, only relying on the data available at Teesside, has been implemented and evaluated, however it was not performant enough to meet operational objectives. However, part of the developments performed were

successfully used by EDF to help the development of performance models on its wind turbine fleet (outside from ROMEO scope).

- Main bearing: the main bearing faces many degradation types such as micropitting, debris damage, cage failure, roller edge loading, etc. A diagnosis and prognosis physical algorithm has been developed based on the CMS data. This algorithm has been enriched by a decision support model accounting for patterns in the physical algorithm outputs. Without main bearing failure observed at Teesside wind farm, the evaluation process conducted provides only preliminary results. Despite false positive having been observed from the direct output of the physical algorithm, a significant part of these false positive were filtered out by the decision support model. It however points out the need to adapt further the classification methodology with the associated thresholds. EDF has a strong confidence in the methodology implemented and has in view to perform the appropriate adaptations once a failure event will be reported.
- Gearbox: the aim of the algorithm developed by EDF, based on the CMS data, is to detect early enough incipient fault within the gearbox, be it on the high speed part, intermediate speed part or low speed part. The algorithm developed has been efficiently tested and evaluated based on the available data, notably relying on one failure event duly reported at Teesside corresponding to a planetary degradation. Nevertheless the extent of the evaluation has been reduced by the available CMS data, stressing out, for the purpose of evaluation, the inadequacy of the data retaining policy with an half life of 6 months. The methodology developed is thought to be robust by EDF, with however beneficial adaptations identified to better address the variety of failure modes. Outside from ROMEO project scope, complementary work is conducted out by EDF for diagnosis & prognosis of gearbox failure modes on the whole wind turbine fleet.
- Transformer: the aim of the algorithm developed is to detect incipient fault within the transformer be it for instance associated to a degradation of the insulation within transformer coils, or degradation of the transformer cooling system. The evaluation period for the algorithm ranges from 2014 to end 2021, with 25 events identified. This evaluation has shown satisfactory performance results with an accuracy of 93.3%, a recall rate of 3.1%, a precision of 63.3% and a rate of false positive of 0.1%. It has confirmed the positive economic evaluation of the use of the algorithm, that is being implemented on the EDF wind turbine fleet in 2022.

  Generator: the aim of the algorithm developed is to detect incipient fault within the generator, be it related to the stator windings, to the squirrel cage rotor bars, or to the cooling system. Two methodologies have been developed and implemented to accommodate with different types of data available. No failure events having been observed at Teesside, the extent of the evaluation at Teesside wind farm has been limited, with no false positive observed. Nevertheless, following the developments, EDF has successfully evaluated the algorithm on onshore wind turbines with observed abnormalities and implemented it on the EDF wind turbines fleet in 2021. A patenting process has been launched on generator diagnosis (« Procédé, dispositif et système de surveillance d’une machine électrique tournante », FR1913058).

Figure 22. Teesside offshore windfarm.

- SG Wikinger : Wikinger is composed of 70 wind turbines of 5MW. They are an hybrid gearbox with synchronous generator and full converter. The windfarm, owned by Iberdrola, is operating since mid-2018 and it served as a place holder of different investigations within ROMEO, and also for data collection of SCADA and vibration data in order to perform different monitoring jobs. The windfarm has a Bachmann CMS and it is limited to the existing monitoring capabilities. For this operational windfarm, diagnosis and prognosis algorithms have been developed, implemented and evaluated on a daily basis:
  - Gearbox trends: Sliding bearing failures can only be detected with thermal trends by using the present arrangement. Models have been arranged and put in place for daily monitoring.
  - Blade/pitch system: Regarding blade bearing, models have been put in place in order to monitor roller or lane damage together with structural integrity potential failures. In this case, due to lack of data, only protective algorithms could be put in place.
  - Converter: Converter algorithms allow for an increased diagnosis and prognosis of converter failures, allowing for some maintenance tasks to be avoided and better diagnosis and isolation of failures.
  - Generator: Synchronous machines are now better monitored by calculating the deviation from design parameters together with the status of health of the windings.
  - Gearbox gears and inner bearings: In cases of determinate stages of the gearbox failing, the detector would trigger and allow for better diagnosis together with the CMS and visual inspections.
  - Main bearing: Same as gearbox, especially when failures are close, this algorithm allows to attain better isolation and identification of the failure, as well as an accurate timing for failure occurrence.

- Transformer: Given the story of transformers it has been interesting to profile structurally the remaining life together with the capability of detecting failures.

In all cases, Siemens Gamesa process for module development was:

First of all, making a consensus of the initial failure mode effects and criticality analysis, but complemented with the experts that would work on the diagnosis development.

Once the consensus was achieved, making clear that the workflow involved a diagnosis technical person writing the code and the method, and having aid from one or two specialists from the electrical and mechanical area.

Framework for (Module) operation

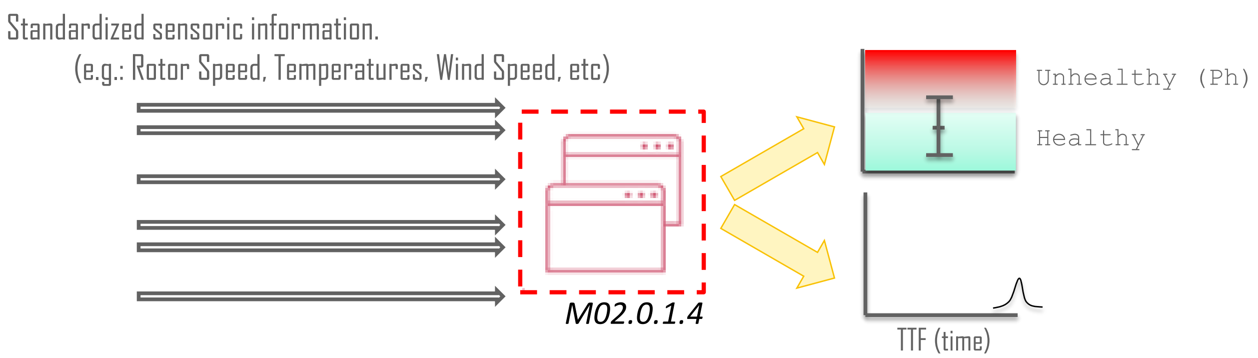


Figure 23. Framework of Module operation figure.

Finally, the module would be fitted into a framework (see simplied version in Figure 23) were data input was all SCADA data (for convenience and using all data available), together with an output, which was standardized to the following:

> <WindTurbine [integer]>|<module identifier [string]>|<diagnosis phase <int>|<diagnosis confidence [float 0-1]|<prognosis TTF in days [int]|<prognosis confidence [float 0-1]>|<timestamp execution [UTC Z date format]>|<time stamp last SCADA [UTC Z date format]>|<RDS-PP [string]>|<optional health indicator [float 0-1]>

Once the algorithms were ready, a potential add on for each module was to plot a particular visual method in order to make the analyst aware of the status of health.

The entire process has been documented and attached to D3.1 as well as compiled into deliverables that would be sent to the cloud computer environment.

3.3.2. Machine Learning Models

As part of ROMEO project, machine learning models for major components were developed and tested. The models developed are covering, to the extent possible due to data availability, Wikinger and East Anglia One wind farms owned by Iberdrola, and Teesside owned by EDF.
The process started by selecting the most important features for each of the analysed failure cases.

- Feature Selection
    - The main feature selection for ML models was done through discussions with the operators and manufacturers of the Wind Turbines. These experts manually selected SCADA features per failure mode from the SCADA data, and gave valuable insights into the processing of the frequency domain data coming from the CMS systems. That data was further pre-processed so fit the requirements of the ML models.
- Once features were selected, degradation models for wind turbines were developed:
    - In this project two types of ML failure models were developed. The first type is an Anomaly detection autoencoder model, and the second type is a forecasting model based on temporal convolutional neural networks (TCN). Both these models work specifically with convolutional layers CNN, therefore they are both based on convolutional neural networks which in this case of the ROMEO failure models were a better fit over the Recurrent neural network RNN based models. This is because CNNs give us a greater control when working with multivariate time series. This is mainly because these type networks use deep learning layers which can consider all the features at once, which allows the models to encode intra feature dependencies, all while considering multiple time step inputs. Therefore these CNN based models are able to highlight the individual feature contributions along with the intra feature contributions across time.
- Finally, an effort has been done, for explainability of results to wind farm operators to take more informed decisions.
    - Regarding the explainability of the ML models, an algorithm was developed which help interpret the results of the anomaly detection models. This algorithm mainly highlights the contribution of each feature to the detection of an anomaly. This quantifies the anomaly's overall error in terms of features, therefore support personnel along with the operators of the wind turbines can use such information in order to further post-process the anomalies. This can be done through a decision making systems which validates anomalies based on the features involved for that anomaly along with the percentage of their contribution. An example is provided below.

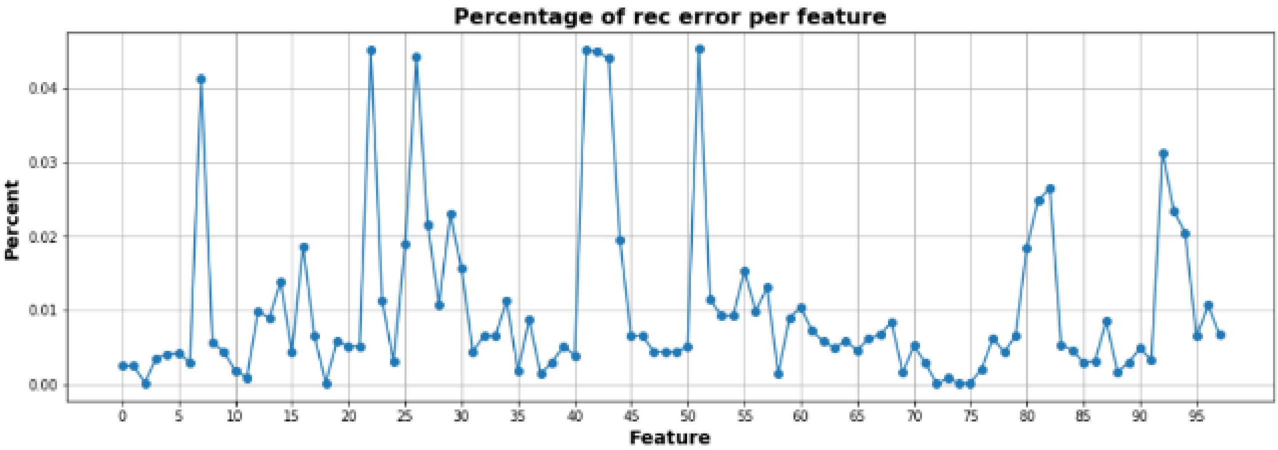


Figure 24: Feature contribution on the anomaly

Figure 24 shows a scaled version of contribution from 95+ features quantifying the effect and contribution of each of them on an anomaly. These are provided in a ranked list from most contributing to least contributing features.

Furthermore, additional work regarding explainable ML models has been carried out, regarding feature analysis. This work is described in detail below.

3.3.2.1. Explainable Degradation Detection

Being able to detect whether the performance of a wind turbine is degrading is an important step towards increasing the amount of energy produced by wind farms. Through the case studies developed in ROMEO, it was possible to compute an explainable decision tree that allows the degradation detection of wind farms with high accuracy. In fact, it is shown that we can detect whether a wind turbine is degrading or not by simply checking whether a set of features are above a given threshold or not. These seven feature values hence 'explain' the degradation status of a wind farm.

Our analysis consists of two parts: (1) a data analysis to determine among the many available time series data the ones that could indeed indicate whether a wind turbine is degrading or not, and (2) an approach for detecting the degradation status of wind turbines.

3.3.2.1.1. Data Analysis

The exploratory analysis of component and channel time series has been conducted aiming at:

1. Analysis of the available data. Detection of missing values/periods. Analysis of failures.
2. Understanding general data distribution of the available time series. This is done using boxplots so that the mean, values, 95% quantiles and abnormal values can be seen.
3. Studying the behavior of time series for the whole available period by visualizing them.
4. Detection of the descriptive time series that contain the most variance, have low entropy and do not correlate with others. This time series are going to be the most beneficial for the models of degradation and failure detection.

5. Detection whether the time series behavior is similar across wind turbines, or each wind turbine should be considered separately.

The steps followed for data analysis are:
1. Data exploration
2. Time series exploration
3. Aggregation periods
4. Descriptive time series detection
5. Time series behaviour across WTs

There are several considerations that need to be taken into account during data exploration:
- Correlated time series: For better modeling the non-discriminative time series should be removed.
- Missing data: These dates were omitted from consideration.
- Labeling data: the degradation periods are defined based on known O&M events on the WTs.
- There are many wind turbines with a small number or none degradation periods which can make it difficult to build per turbine models of failure/degradation detection.

From the time series depicted in Figure 25, it can be noticed that there are many highly correlated time series for WT1[12].

[12] Exact location of wind turbine concealed due to confidentiality

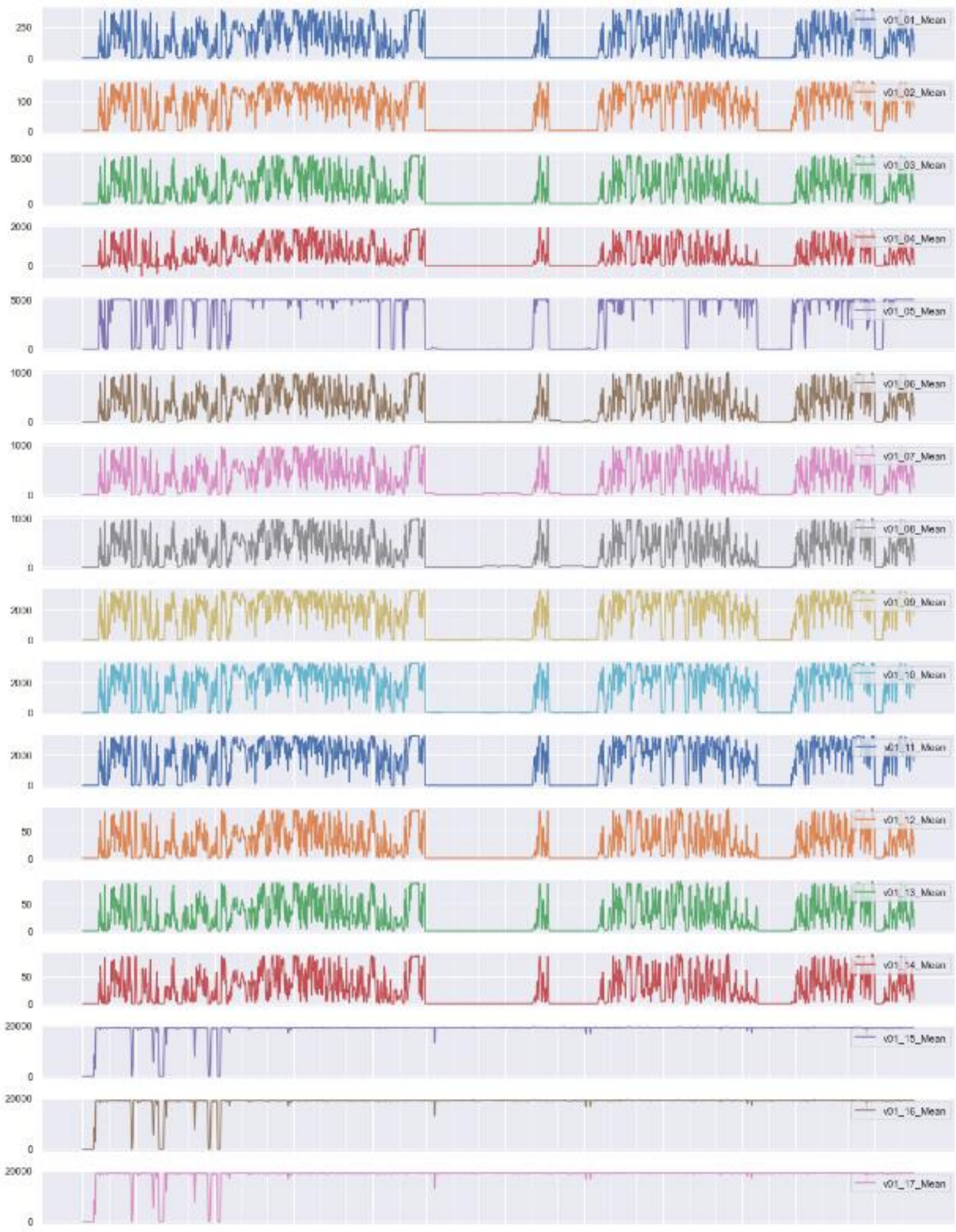


Figure 25: Time series of various channels of component 1 from one WT.

In order to detect the descriptive times series of component, channel pairs we have considered first the entropy of time series, aiming at keeping the time series with enough variability. For example, on Figure 26Figure 25. the upper two time series have enough variability while the lower two have low variability and, thus, were excluded from the list of descriptive time series for failure modelling.

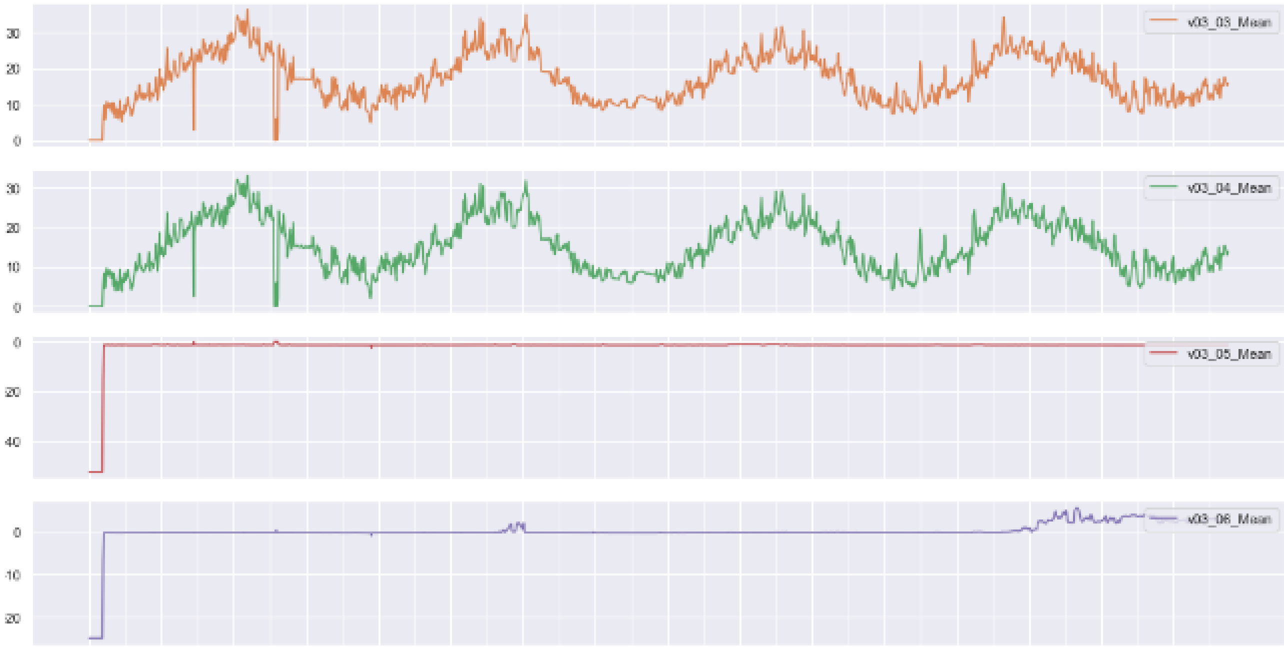


Figure 26: Time series v03_05 and V03_06 were excluded from consideration due to high entropy.

Second, we kept the time series that are independent enough from the rest. The independence was measured in terms of covariance between the time series. If two time series have covariance higher than 0.9, one of them is removed from consideration as it does not bring new information to the model. The example of covariance matrix can be seen on Figure 27. Following this process, the components and associated time series are described.

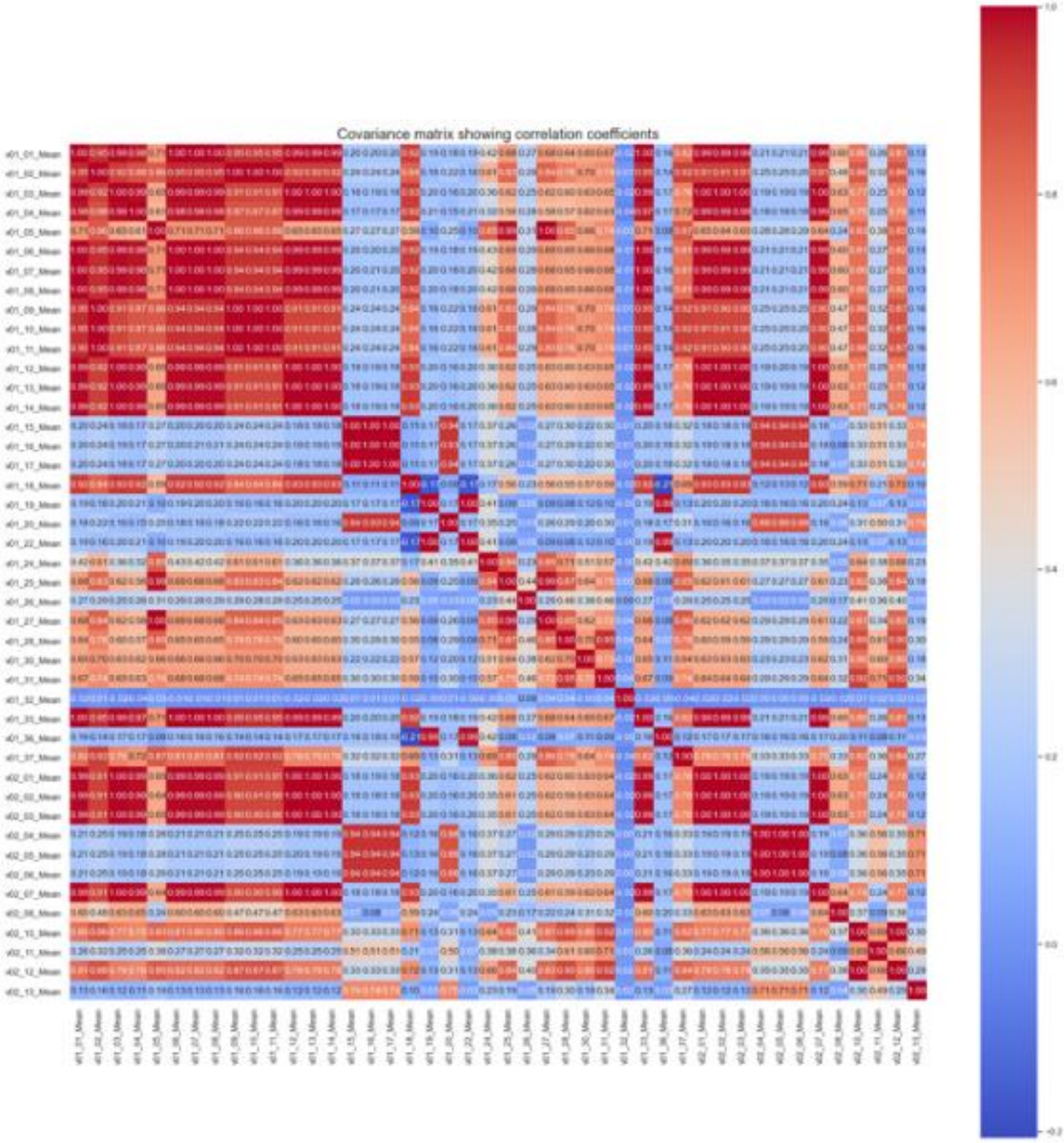


Figure 27: Covariance matrix of various channels of component 1 and 2 for WT1.

While doing the time series analysis for informative or descriptive time series detection, we have observed that for different wind turbines the set of informative times series might be different, even though it overlaps to a great extent. This means that indeed the modelling should be done for each wind turbine separately. Due to the lack of labelled failures for all the data, it still makes sense to do the overall modelling, but in this case the time series of interest should be the intersection of descriptive time series between all the wind turbines.

Exploratory analysis of the data and search of the descriptive time series led to the following conclusions:

1. Time series of the component, channel pairs are not always informative as many of them are correlated, and some contain low information for modelling.
2. Time series aggregation can be done for 1 day of observations, courser granularity is also possible, if necessary, but it does not influence much data distribution.

3. There is evidence that failure/degradation models should be built for each wind turbine separately if sufficient data is available, since descriptive time series vary from turbine to turbine.
4. The number of labelled failures might be not high enough in order to capture abnormalities per wind turbine. In this case, wind farm level models should be considered.

In further analysis, we will see if the descriptive features are powerful enough to build failure/degradation prediction models for each wind turbine separately in the presence of the limited amount of labelled data.

3.3.2.1.2. Degradation Detection

As shown in previous section, deep learning models were used to detect failures in wind turbine operation. These models considered normal and degradation periods across all the wind turbines for training. Given the analysis of time series and their slightly different behaviour for each wind turbine, in this study for the possibility of personalized 'per turbine' degradation classification is checked. Then, it is assessed whether the model can be transferred to other wind turbines for degradation detection.

The well-known drawback of deep learning models, like the ones used before, is that they lack explainability. This section focuses on the models with high explainability, such as decision trees, and on the model that reaches the same performance for multivariate time series classification as deep learning models but has partial explainability. These are random forest (RF) classifiers [1]. Even though RF classifiers do not provide a clear set of rules as decision trees (DT) do, they still provide better interpretability by detecting the most important features by means of feature purity analysis.

Classification models for degradation detection are built for a WT with a high amount ground truth degradation data. This will be referred as WT2.

Following the work of Baldán and Benítez [1], the vectors of complexity measures and features for multivariate time series (MV_{TS}) are built. In our case, the features that describe the distribution of time series values and correlation-aware time series characteristics were used. The characteristics that we used are described in Table 2. There are more explainable time series features that potentially could be exploited for degradation detection, but according to the exploratory analysis of time series made in the previous section, we focused on the subset in Table 2.

Table 2: Time series distribution and self-correlation features used for degradation detection.

Feature Name	Description	Range
10%, 50% and 90% Quantiles	Determines how many values in a distribution are above or below a certain limit, 50% quantile is a median	Domain of time series values
Skew	Measures asymmetry of the probability distribtution	$(-\infty,\infty)$

Kurtosis	Measures the degree of tails of the probability distribution	(-∞,∞)
Trend	Strength of trend	[0, 1]
Entropy	Measure of variance of time series	[0, ∞)
Autocorrelation coefficient with the correlation lag = {2, 3, 4}	Finds correlation patterns inside the same time series	[-1, 1]

Figure 28 shows the workflow of multivariate time series pre-processing. First, there is a sample of *n* multivariate time series consisting of m components each. The next step is the calculation of time series features for each of the *m* components. This way the n initial multivariate time series are transformed to be represented by *m* vectors of calculated features. As a final pre-processing step, all the features that belong to the same MV_{TS} are concatenated, namely, placed in the same raw. This forms the part of the same instance and is ready to be processed by any classifier of choice as the obtained sample attributes are transformed into vectorial shapes.

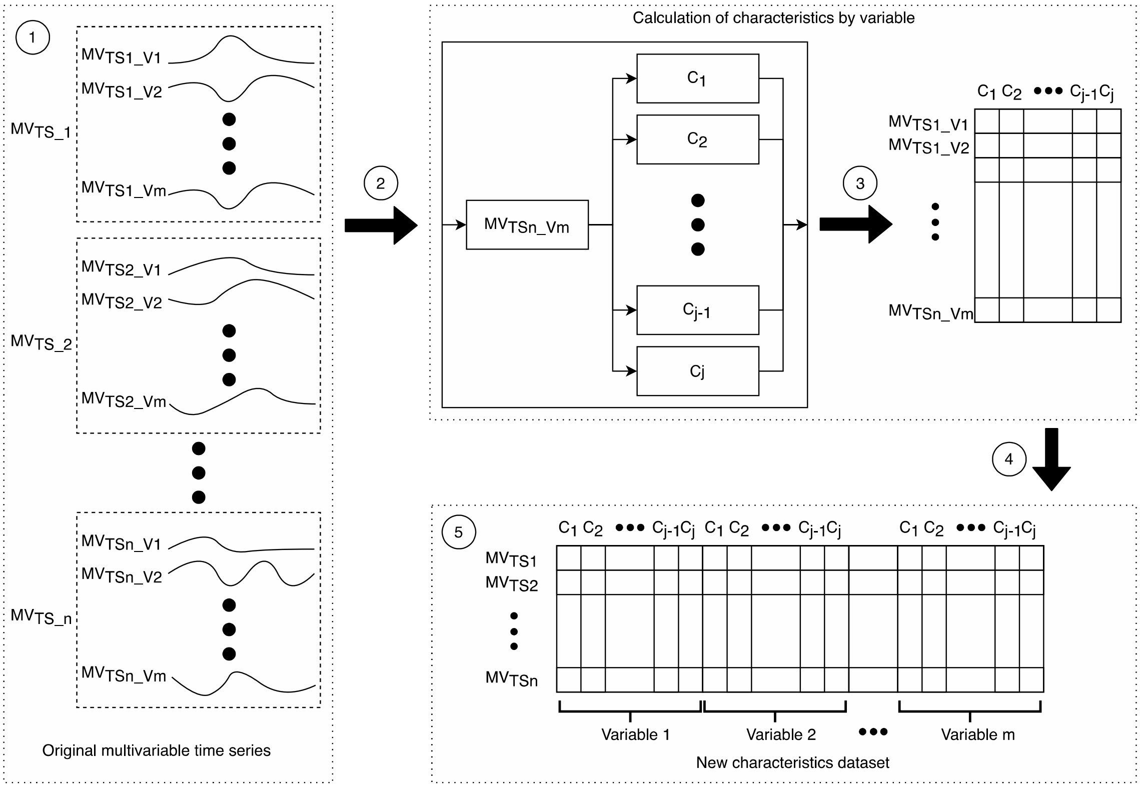


Figure 28: Features calculation workflow [1].

3.3.2.1.2.1. Decision Trees and Random Forests

Two classifiers that perform well for multivariate time series in the literature and have good explainability properties, are Decision Tree and Random Forest classifiers. To assess the performance of classifiers we split the pre-processed time series into train and test sets using stratified reshuffled splits.

Stratification is done based on the labels, so the percentage of the 'Normal' and 'Degradation' samples are the same through the splits.

We estimate the following performance measures of a classifier:

1. For each label, namely 'Normal' and 'Degradation' label, we assess:
    a. $Precision = tp/(tp + fp)$, which calculates the number of correct results divided by the number of all returned results.
    b. $Recall = tp/(tp + fn)$, which is the number of correct results divided by the number of results that should have been returned.
    c. $F1 - score = 2 * precision * recall/(precision + recall)$, is a combination and harmonic mean of precision and recall that is often used in the circumstances when both precision and recall are important
    d. Support – is the number of samples per class in the test set.

2. We measure overall classification accuracy: $Accuracy = (tp + tn)/(tp + tn + fp + fn)$, which is the ratio of the correct classified samples overall.
3. As traditional accuracy is misleading for the imbalanced datasets, which is our case as the number of samples with normal behavior is much higher than the number of degradation samples. We also consider macro average and weighted average where the performance measures for classes are combined considering their support.
    a. The macro-averaged scores are computed by taking the arithmetic mean (aka unweighted mean) of all the per-class scores.
    b. The weighted-averaged scores are calculated by taking the mean of all per-class scores while considering each class's support.

Tp, tn, fp, fn - - are the number of true positives, true negatives, false positives, and false negatives per class correspondingly. The process is repeated 20 times with different random splits to estimate the cross-validation results.

The results for one run for the decision tree classifier for the degradation detection task for WT2 are shown in Table 3. There are 47 time series and 10 features for each time series in this model. The 20 cross-validation results can be seen in Figure 29.

Table 3: Performance assessment of decision trees classifier for degradation detection for WT2.

	precision	recall	f1-score	support
normal	0.99	1.00	0.99	280
degradation	0.96	0.92	0.94	26
accuracy			0.99	306
macro avg	0.98	0.96	0.97	306
weighted avg	0.99	0.99	0.99	306

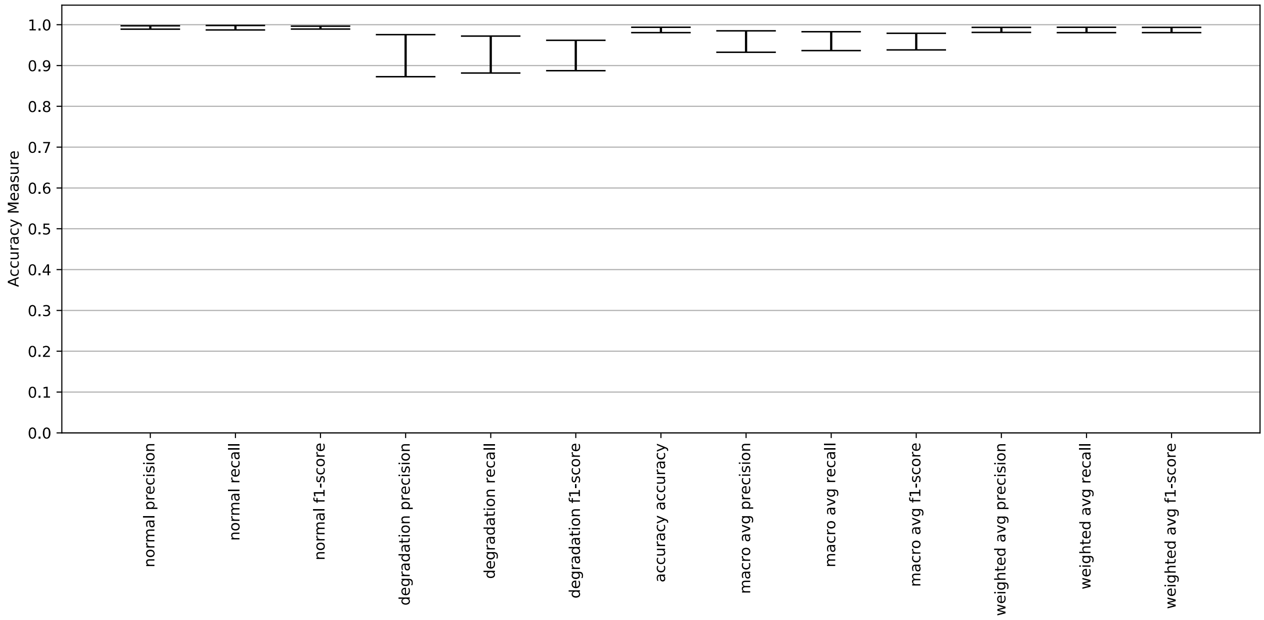


Figure 29: Average and standard deviation intervals of 20 cross-validations for decision tree classifier.

We can see that the 'Degradation' class is detected and retrieved on average in 93% of the cases, as both average precision and recall are around 92.5%.

This degradation recall can be further elaborated, if the final user finds the explainability part of decision trees more valuable. Visualization of decision tree rules, which are produced by the decision tree with performance measures from Table 3, is represented in Figure 30. The first row in each node states the condition to be checked (e.g. v10_05_Mean 10% quantile <= 37.794). If this condition is true, the left arrow is followed and the condition of that node is analysed. Otherwise, the right arrow is followed. The procedure is repeated a leave node is reached. The last line of leave nodes states the label ("normal" or "degradation").

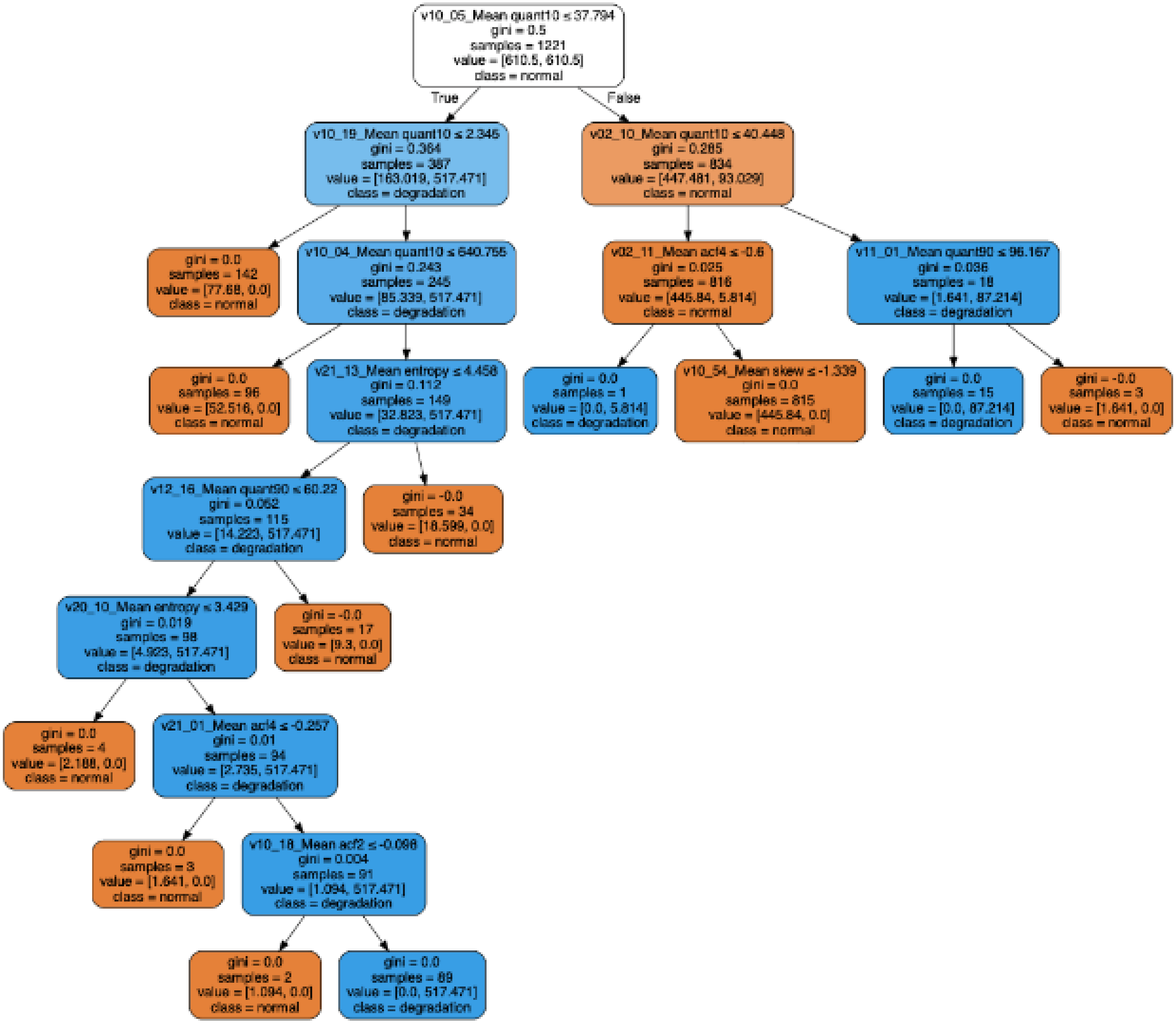


Figure 30: Decision tree rules for degradation detection.

As already mentioned, there are 47 time series and 10 features for each time series in the model depicted in Figure 30. As we can see from the plot out of 47x10 multivariate time series features, the following are important for DT classifier:

1. V10_05_Mean 10% quantile;
2. V10_19_Mean 10% quantile;
3. V10_04_Mean 10% quantile;
4. V21_13_Mean entropy;
5. V12_16_Mean 90% quantile;
6. V20_10_Mean entropy;
7. V21_01_Mean autocorrelation coefficient (acf) with lag 4;
8. V10_18_Mean autocorrelation coefficient with lag 2;
9. V02_10_Mean 10% quantile;
10. V01_11_Mean autocorrelation coefficient with lag 4;
11. V10_54_Mean skew;
12. V11_01_Mean 90% quantile.

As we can see there is quite an impressive performance for a decision tree with only 12 parameters.

The main time series features of importance are:

- 10% quantile;
- 90% quantile;
- entropy;
- autocorrelation coefficient with lag 4;
- autocorrelation coefficient with lag 2;
- skew of the time series distribution.

These features are described in high level in this report due to confidentiality reasons. In reality, these features are often indicators that are connected to physical parameters, making diagnosis and interpretation of machine learning model results more transparent.

As was mentioned in the previous sections, Random Forest classifier is the state-of-the-art method for multivariate time series classification that also provides a certain level of explainability.

First, we report the performance of one Random Forest (Table 4) as in the previous case, and then show the results of 20 cross-validation experiments (Figure 9).

Table 4: Performance assessment of random forest classifier for degradation detection for WT2.

	precision	recall	f1-score	support
normal	1.00	1.00	1.00	280
degradation	1.00	0.96	0.98	26
accuracy			1.00	306
macro avg	1.00	0.98	0.99	306
weighted avg	1.00	1.00	1.00	306

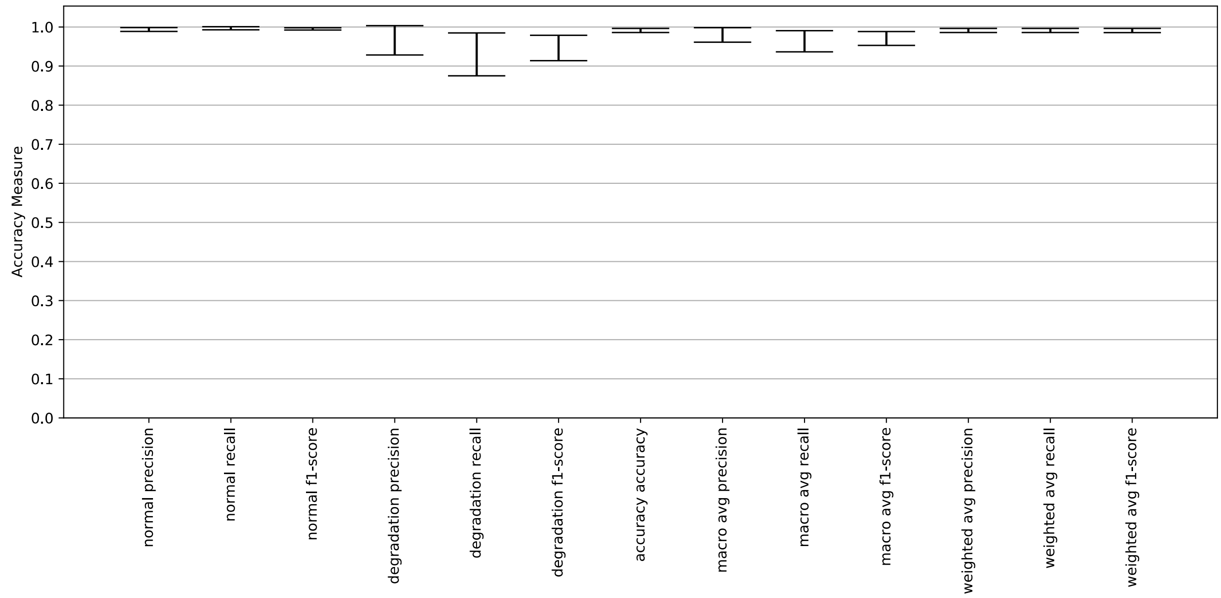


Figure 31: Average and standard deviation of 20 cross-validations for random forest classifier.

All the accuracy measures for RF classifier are higher than for decision tree classifier, even though the difference in one of the most important measures, such as degradation recall and macro average recall, is very small (for example, 93% versus 92.5% for degradation recall), and are not different statistically significantly. All the other metrics have higher average and tighter confidence intervals.

Unfortunately, RF does not provide a clear set of rules as decision trees do, but it allows to determine the most important descriptive features based on their mean decrease in impurity.

As there are 47x10 features that we have tried, we show only a sample of important features (Figure 32) and then summarize the rest. The higher is the mean decrease in impurity, the more important the corresponding feature is.

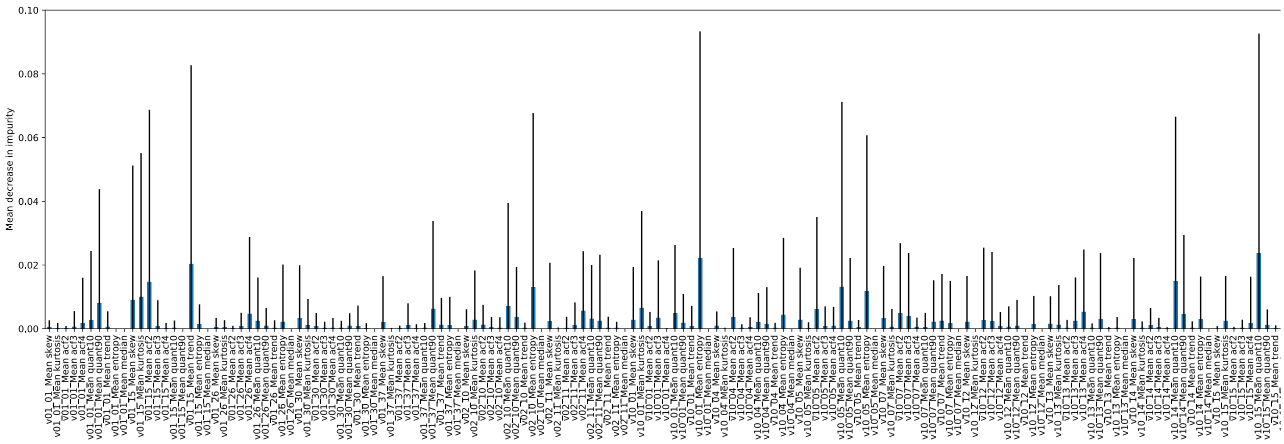


Figure 32: Sample of mean decrease in impurity by random forest classifier.

Based on the impurity analysis the following time series features are important for RF overall:

- Trend;

- Entropy;
- 10 % quantile;
- 90% quantile;
- Autocorrelation coefficient with lag 2, 3 and 4;
- Skew.

Basically, in addition to the important features selected by decision trees, the strength of trend is added as important.

On the other hand, the following time series components show the greatest importance:

1. v01_15_Mean
2. v02_10_Mean
3. v10_01_Mean
4. v10_05_Mean
5. v10_14_Mean
6. v10_15_Mean
7. v10_43_Mean
8. v11_01_Mean
9. v11_14_Mean
10. v20_10_Mean
11. v20_12_Mean
12. v20_29_Mean
13. v21_01_Mean
14. v21_04_Mean
15. v21_09_Mean
16. v21_14_Mean
17. v21_16_Mean

These are 17 components out of 47, for the decision tree classifier, there were 12 components. They intersect to a certain extent but not that much as the Random Forest is mostly focused on the trend and entropy components, whilst decision trees were considering quantiles and autocorrelation coefficients the most.

3.3.2.1.2.2. Model Transfer to other Wind Turbines and Combining Wind Turbine Data

This section investigates how the models learned for wind turbine WT2 perform on other wind turbines where we have less ground truth degradation data.

The initial hypothesis is that model transfer is applicable in case the wind turbine has the same failure modes as the initial wind turbine used for model training.
For this purpose, we consider wind turbine WT3 with same failure types in the same component at WT2.The results of RD and DT classifiers are similar in this case. The classifiers can predict normal behaviour quite accurately but completely miss the degradation labels (Table 5).

Table 5: Performance assessment of DT classifier trained for WT2 and assessed for WT3.

	precision	recall	f1-score	support
normal	0.91	0.98	0.95	1396
degradation	0.04	0.01	0.01	72
accuracy			0.90	1527
macro avg	0.48	0.50	0.48	1527
weighted avg	0.84	0.90	0.87	1527

The poor results for degradation classification in transferal models can be connected also to the low number of available degradation periods which means that the model has not seen enough degradation types through all the turbines.

The failure of the models transfer to the other wind turbines might be also explained by the fact that the component-time series with the same label had different behavior, correlation with the rest, and discriminative importance in general. It seems that each wind turbine has its own characteristics and, thus, the data from the wind turbine of interest should be also used for training.

Following the strategy of the deep learning modelling that took place in the project before, we are going to train and assess the model on the combined data, for the three wind turbines that we have checked so far and see if the combined model performs well and whether it outperforms personalized models.

For comparison purposes, the results of one RF classifier trained and tested for WT4 are shown in Table 6.

Table 6: Performance assessment of RF classifier trained and tested for WT4.

	precision	recall	f1-score	support
normal	1.00	0.99	1.00	245
degradation	0.97	1.00	0.98	61
accuracy			0.99	306
macro avg	0.98	1.00	0.99	306
weighted avg	0.99	0.99	0.99	306

We would like to check if the classification performance improves when we use the data from the other wind turbines, namely WT2 and WT3 together with the training data for WT4 to predict degradation periods for WT4 similarly as done in the deep learning models. The results of this experiment are shown in Table 7.

Table 7: Performance assessment of RF classifier trained on WT2, WT3, and WT4, and tested for WT4.

	precision	recall	f1-score	support
normal	1.00	1.00	1.00	245

degradation	0.98	1.00	0.99	61
accuracy			1.00	306
macro avg	0.99	1.00	0.99	306
weighted avg	1.00	1.00	1.00	306

Indeed, all the measures stayed at their highest or improved, which means that the training data from other wind turbines helped but as we have seen before the training data from the wind turbine of interest is of the main importance.

Similar effect happens when we train on all three wind turbines and test only for T011, all the average performance measures are slightly higher (Table 8).

Table 8: Average performance results comparison of RF classifier trained on 3 and 1 wind turbine correspondingly and tested for WT2.

	Normal			Degradation		
	precision	recall	F1	precision	recall	F1
Trained on 3 WTs	99.45	99.8	99.63	97.85	94.03	95.86
Trained only on WT2	99.38	99.71	99.55	96.89	93.27	94.94

The degradation detection study with explainable classification methods led to the following results:

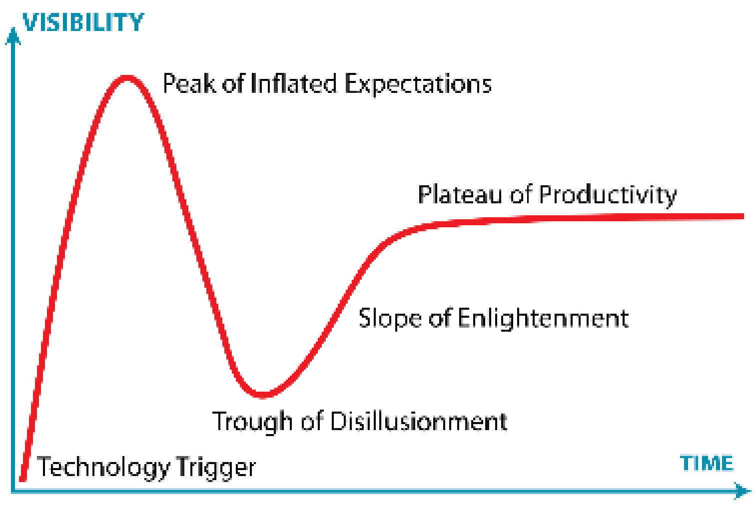
1. Time series components that were extracted in the previous section during exploratory analysis indeed have good descriptive power and can explain degradation periods with high accuracy. We could reach degradation recall of 95% for all personalized wind turbine models that we have tried. The combined models demonstrate even higher accuracy values.
2. In this study, we considered the state-of-the-art method for multivariate time series feature extraction that first of all, leads to sensible distributional and intra-correlation-aware explainable time series features, and second, allows the use of degradation classification models with high performance and full (decision tree models) or partial (random forest models) explainability.
3. During the study, the most significant multivariate time series components were detected together with the most influential time-series features. This information can be used for the model refinement if the approach will be adopted for the usage by the Wikinger wind farm.
4. The degradation detection study has also validated the previous deep learning modeling approach where the data was used for all the wind turbines to predict the failures of a particular wind turbine. This indeed leads to more accurate models as, otherwise, the ground truth data of failures is very limited which leads to bounded personalized wind turbine models together with a constrained model transfer directly from one wind turbine to another.

3.4. Digital Twins for Asset Management

Digital twins have received major attention in the past 2-5 years (2017-2022) also reflected in the positioning of "the" digital twin in Gartner's "Hypecycle for the internet of things" over the last years (see Figure 33). Yet, "(…) there is still no uniform definition of digital twins"[13] and there will, most probably, be no uniform definition of digital twins, due to the different targets and markets in general. We favour a general description of a digital twin above a detailed declination. This by being defined through automated information flow from physical to digital object and vice versa. While the first part, capturing information from physical objects and bringing it to the digital world is executed in countless applications, implementing a digital twin and hence transferring gained information back to the physical worlds is often not achieved – we consider such approaches "digital models" or "digital shadows" in accordance with Kritzinger [14].

Ramboll has a long-lasting history in re-assessments of assets (structures), starting back in the 1990s. Over the last three decades, a profound and certified procedure has been developed and applied. This procedure was adjusted and transferred to offshore wind structures in ROMEO. Today this procedure has become the central piece of the digital twin technology for offshore foundations. That said, there are several other applications, such as virtual reality and map-based representations for data documentation management, training, and on-site support.

Digital twins in offshore wind, more precisely, digital twins representing the support structure of offshore wind turbines, are used for a variety of reasons. They comprise the goal to reduce offshore work time, increase asset availability and hence power production, monitoring the integrity, and enable lifetime management by achieving lifetime extension.



[13] Digital.Trend.Studie Digital Twin – Zwischen den Welten - Potential, Reifegrad und Einsatzgebiete Digitaler Zwillinge für die DB; DB Systel GmbH; 2020/09

[14] Source: W. Kritzinger, M. Karner, G. Traar, J. Henjes, and W. Sihn, "Digital Twin in manufacturing: A categorical literature review and classification," *IFAC-PapersOnLine*, vol. 51, no. 11, pp. 1016–1022, 2018.

Figure 33 Gartner hype cycle for new technologies [https://en.wikipedia.org/wiki/Gartner_hype_cycle]. The digital twin reached the "Peak of inflated expectations" between 2018 and 2019 and is now expected to reach the "plateau of productivity" in 2022-2025 [https://www.ergonized.com/blog/iot-in-healthcare/]

3.4.1. Methods and applicability

A digital twin is a virtual representation of a physical object or asset in a digital simulation environment, that provides seamless assistance throughout the lifecycle from the as-designed- over as-built- and as-installed- to the as-is and future states. Originating from design (finite element) models and with a continuous link to operational data, digital twins should be based on a risk-framework (as presented in the preceding sections) and support the operation and maintenance of the physical asset and related condition-based decision making. The digital model can be built from drawings and reports. Ideally, design models are used inside the design environment since this allows for subsequent certifiable re-assessments, design runs, and ultimately decision making.

The process of digital twinning aims to reduce the uncertainties of simulation models by exploiting operational data, mainly measurements but also any other type of information, in a systematic manner. Digital twinning can be thought of as an ongoing process throughout the complete lifetime of the asset, from planning to decommissioning. The governing principle is that physical parameters present in the simulation environment, i.e., structural properties, environmental and operational conditions (EOCs - loads) and their interaction, are assessed or measured at site and transferred to the simulation environment. To do so, as-installed environmental and operational conditions (EOCs) are investigated, and structural modal properties are extracted by fully automated operational modal analyses. Refer to [2] for a more detailed description of the general steps within the digital twin framework for offshore support structures.

Once digital model, operational states, and loads are updated to a satisfying level, direct- and virtual sensing are applied to extract fatigue loads at critical locations. Selecting these locations is not trivial and best executed by subject matter design experts. Fatigue and other loads are tracked over time and accumulated. Based on this analysis a prognosis and scenario analysis for the remaining lifetime is possible. This procedure can be executed either on a campaign- or a continuous- data basis.

Ultimately, Digital twins, once established, should make use of simulation technology that is seamlessly integrated into O&M decision making and risk-based inspection procedures to provide information along the entire life cycle, e.g., supporting operation and service by informing about abnormal structural behaviour, confirmation of structural integrity after extreme events and updating (risk-based) inspection intervals.

The novel implementations and achievements of Digital Twins within the ROMEO project are collected in Deliverable 4.6: Best practice guidelines for future wind farm structural condition monitoring using low-cost monitoring [3].The low-cost monitoring approaches demonstrated within ROMEO facilitate reliability centred maintenance strategies and are summarised below:

1. Reassessment of the simulation models:

    a. FE model update: Modification of the finite element parameters by using measured modal properties of the installed structures.
    b. Wave load calibration: Tuning of wave load coefficients by using measured wave parameters in proximity of the structure.
    c. Fatigue life reassessments: Utilising the updated FE model in combination with the calibrated wave loading, the simulated fatigue life of the structures is extended.
    d. Scenario analyses: Utilising the updated FE model, the influence of scenarios, such as excessive scour, excessive corrosion, and excessive marine growth, on the simulated fatigue life is analysed.
2. Continuous structural health monitoring:
    a. Continuous fatigue monitoring:
        i. Machine learning approaches: Evaluation of fatigue life consumption based on 10-minute SCADA signals for individual structures as well as transferability of those results between populations of structures.
        ii. Modal decomposition and expansion: Continuous evaluation of fatigue life consumption of the entire structure based on a small amount of strategically positioned accelerometers and strain gauges.
    b. Damage detection and localisation scheme for individual structures:
        i. Modal properties tracking: Anomaly detection based on modal properties derived from accelerations.
        ii. Machine learning classification: Anomaly detection and status classification based on 10-minute SCADA signals.

Figure 34 RIAMS – Ramboll intelligent asset management system – displaying digital twin and analysis results.

3.4.2. Population based health monitoring

In conventional structural health monitoring (SHM), a model is developed using data recorded from an individual wind turbine[15]. It is expected to facilitate generalisations on future measurements for that specific system. However, for a single structure, it is usually difficult to have the complete amount of information, usually only a fraction of the information is available for a given structure. Hence, only a fraction of the environmental and damage conditions can be assessed. If a framework can transfer this information from one structure to another one in the population, this will allow for diagnostic inference on the second structure without requiring the same data sources.

The population-based approach to structural health monitoring (PBSHM) aims to transfer valuable knowledge between groups of similar systems. Whether the characteristics of the system are the same or similar within the population is heterogeneous or homogeneous respectively. This type of population will define the degree of transferable knowledge that can be transferred, and by what extend. Great transferability is given for homogeneous populations with non-minimally identical wind turbines. In contrast, heterogeneous populations with disparate members have little to no potential for transferability. By determining the type of population, homogeneous or heterogeneous, a model can be created to represent the behaviours of the population and infer information of fatigue damage between systems. The representation of structures developed is designed firstly to quantify the degree of similarity between the structures and secondly to facilitate the transfer of knowledge via machine learning.

One of the main concepts of conducting PBSHM is that of knowledge transfer. This process is crucial for various reasons. Firstly, conventional methods of data driven SHM using supervised, unsupervised, or semi-supervised machine learning methods assume that the test and training data are drawn from the same distribution. This assumption is questioned in PBSHM as each member of the population will have its characteristics (and hence distribution) because of, e.g., environmental variations, manufacturing, and assembly differences, and/or operational conditions. Therefore, conventional methods begin to fail when models are transferred between systems. For example, one SHM model trained on a 5 MW offshore wind turbine will begin to fail when making predictions on a 1 MW onshore wind turbine since the dynamics are different, but they are from a similar form. Mapping such differences from one member to another is important so that a general classifier can be created.

To establish an effective transfer of knowledge in the context of a wind turbine substructure, one must start by focusing on the responses of a wind turbine from the complex environmental and operational factors. These factors assessed in the context of operation, material, topology, and geometry act as a basis to explain the observed dynamical behaviour differences for the population of wind turbines.

[15] Structural health monitoring; a machine learning perspective. Research Book 2012.

Some studies have been building approaches to deal with PBSHM, the series[16][17][18] carries out a detailed investigation on how to tackle the issue.

3.5. Data Acquisition and Analytics Ecosystem

ROMEO deliverable D5.3 [4] described the data flows that populate the Cloud Object Storage, which is our primary data repository. D5.5 [5] then went on to describe the processing containers that are populated by these flows, and the environment that has been created to enable the ROMEO partners to run analysis of this data and to report their results. The infrastructure in the provider network creates, transforms, and transfers the data in the COS, and the results are then available for use by authorized platforms, especially the Centralised O&M Management Platform.

In ROMEO, we access data objects primarily via either the API[19] or as a simulated file-system mount using S3FS[20]. The API is the most efficient and direct access to the data, but can interact only with the actual COS. Using S3FS gives an interface to the data that is identical to accessing a file on a local storage device, allowing partners to run in production with the exact same code that they have developed using local test files on local storage devices.

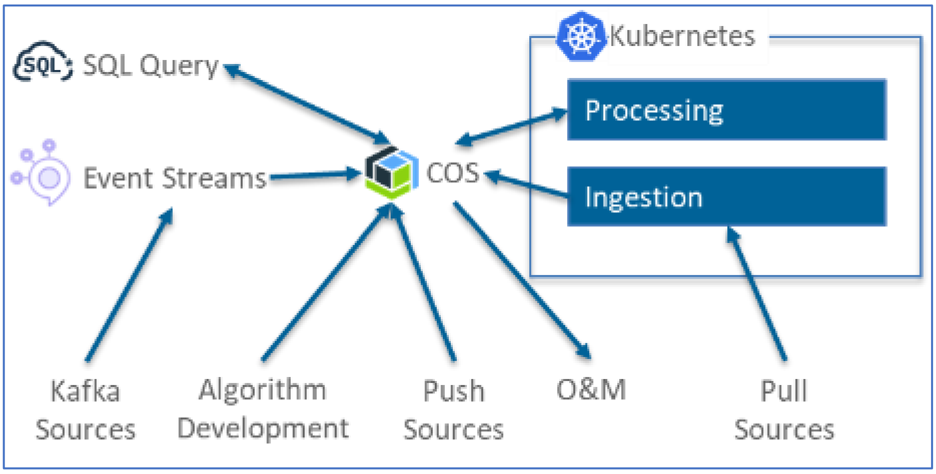


Figure 35: Cloud Data Flows.

By controlling access to each bucket, then using data transformations to move information from one to another, partners can share results while retaining need-to-know access to the raw measurements.

[16] L A Bull, P A Gardner, J Gosliga, T J Rogers, N Dervilis, E J Cross, E Papatheou, A E Maguire, C Campos, and K Worden. Foundations of population-based shm, part i: Homogeneous populations and forms. Mechanical systems and signal processing, 148:107141, 2021

[17] J Gosliga, P A Gardner, L A Bull, N Dervilis, and K Worden. Foundations of population-based shm, part ii: Heterogeneous populations – graphs, networks, and communities. Mechanical systems and signal processing, 148:107144, 2021

[18] P Gardner, L A Bull, J Gosliga, N Dervilis, and K Worden. Foundations of population-based shm, part iii: Heterogeneous populations – mapping and transfer. Mechanical systems and signal processing, 149:107142, 2021

[19] https://cloud.ibm.com/docs/services/cloud-object-storage?topic=cloud-object-storage-compatibility-api

[20] https://github.com/s3fs-fuse/s3fs-fuse

Transformations read data from one bucket, and write to another. One example from the ROMEO environment uses the SQL Service to merge multiple CSV objects into a reporting object used by the O&M service. This import is triggered after every successful import of fresh data to the input bucket, and serves to simplify the retrieval to a single object per day while also reducing the bandwitdth required for the transfer. This transfer also serves to limit the data served to the external service, minimizing the scope of data exposure to those values required by for reporting.

The most complex transformations are actual data analysis solutions, which are deployed in containers executing in a Kubernetes instance in the IBM Cloud. Containers are built in layers from a base image to a complete description of a fully configured virtual machine. These analysis containers are based on an image that mounts COS on the local file system, and are then extended to include the analysis code.

A separate Kubernetes environment exists for each test site. These environments contain "secrets," which are small storage objects containing credentials for accessing COS or other resources. Secrets are linked to specific containers, based on requirements. Containers can access only those secrets that have been assigned to that container. More detail about these environments has been provided in D5.5.

3.5.1. Edge Computing Infrastructure

The name Onesait Platform Things Edge-Node is used for all products developed by Minsait / Indra and that meet the architectural requirements to be deployed on Node#1 devices.

In the domain of the ROMEO project, when using a device node#1, the solutions that are used for the acquisition of signals and on which to perform a processing, must comply with the architecture and requirements defined in the scope of said denomination.

3.5.1.1. What is Edge Computing?

The word "Edge" in this context means literally, a geographic distribution. Wikipedia defines Edge Computing as "pushing the frontier of computing applications, data, and services away from centralized nodes to the logical extremes of a network. It enables analytics and data gathering to occur at the source of the data". The architectures based on Edge Computing, solves two important well known problems that have arisen in the deployment of the traditional IoT(i) the volume problem of information and (ii) the latency problem in the assisted or automatic decision. Only recently and due to the consideration of security and privacy in the IoT data exchanged, a third problem has been acquiring notoriety, the problem of local information:

- According with the first problem, the amount of information produced by an IoT system grows exponentially, however, the need for computing capacity to process that information also grows exponentially, but much faster, causing data to be left untreated. Additionally, the bandwidth of the installations and sites is always finite and although it can be increased (with its corresponding increase in cost), there is no capacity for it to grow as much as the total volume of information.

- The second problem is based on the physical fact according to which, moving information always takes time, proportional to the distance between sender and receiver. In the new scenarios of use envisaged by the extension of the 5G network, the capacity of management in mission critical or self-controlled systems with latencies below seconds, require a nearby computing that cannot delay calculations to be performed in a distant infrastructure (cloud), kilometers away from where the final action should be implemented.
- Finally, the last problem reveals that a good way to protect information, which due to its sensitivity or importance to the business must be kept as private, is limiting its dissemination as much as possible, which can be efficiently achieved if it is processed locally, that's, where it was generated.

The Edge Computing architectures focus on solving these problems, minimizing the information that is actually moved among the components, optimizing the use of expensive resources such as communication and distributing the processing capacity in a coordinated manner. However, Edge Computing architectures are not the solutions to all the problems that deployment of IoT systems entails. In fact, their management and governance are much more complicated that IoT cloud first approach.

3.5.1.2. Main functions of the Edge Computing

Distributed processing and storage as well as fast service delivery following a multi-layer approach are the key functions that enable IT/OT integration thanks to Edge Computing.

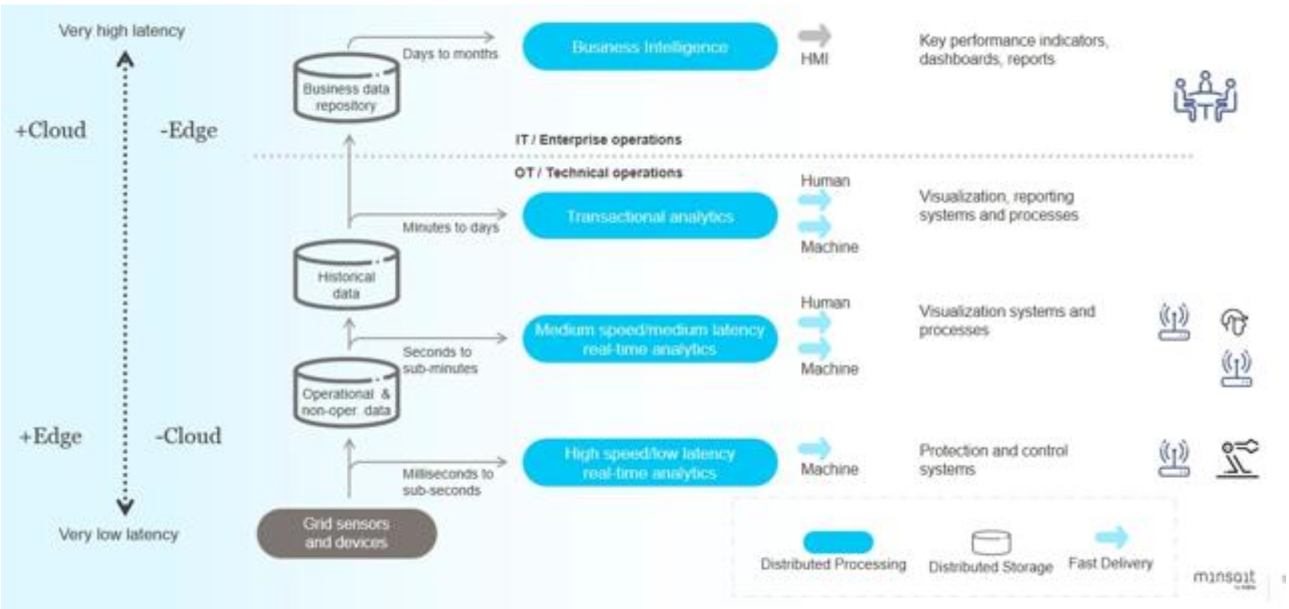


Figure 36: Main Edge Computing functions

There is a very important aspect to mention when considering the new architectures of Edge Computing, its capability for flexible adaptation and resilience. A scheme like the one presented above is also compatible with the deployment of traditional operation technology based on automation equipment (PLC, for example) and SCADA systems linked with IoT or IIoT cloud platforms. However, Edge Computing architectures rely on the virtualization of the hardware function wherever it occurs.

This virtualization can be done in many ways using different languages, frameworks, data models and components bundle most of them open, unlike the protocols and processes implemented by each equipment manufacturer. Edge Computing enables the application of "software defined hardware" scheme, allowing to change the behavior of the devices thanks to a slight modification of the software deployed, as opposed to a more traditional approach that requires the replacement of the embedded firmware.

3.5.1.3. Node#1 Architecture

The concretion of the Onesait Platform Things Edge-Node architecture is the following:

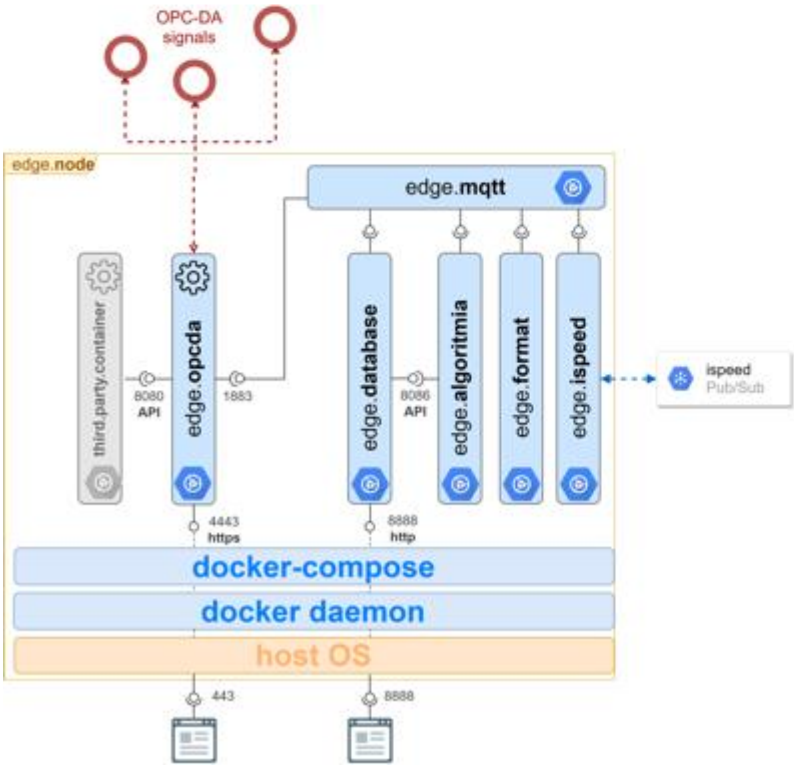


Figure 37: Edge-Node architecture

It has 5 intercommunicated containers through the MQTT broker mentioned in the previous section. The "edge.opcda" container is responsible for the acquisition of UCC SCADA Server (Iberdrola) signals through the OPC DA protocol and its subsequent publication in the "edge.mqtt" container. The containers subscribed to the topic where the UCC signals are published are "edge.database" as a signal storage and data source for the container of "edge.algorithmia", "edge.format" as transformation and signal algorithm and application of rules and "edge.ispeed" as a consumer of signals to be sent to the platform.

With all of them not only the acquisition of UCC SCADA Server signals (Iberdrola) through OPC DA and shipping to the platform through the ispeed container is covered, but also allow the application of algorithms, signal processing and the necessary calculation in the edge database, algorithm and format containers.

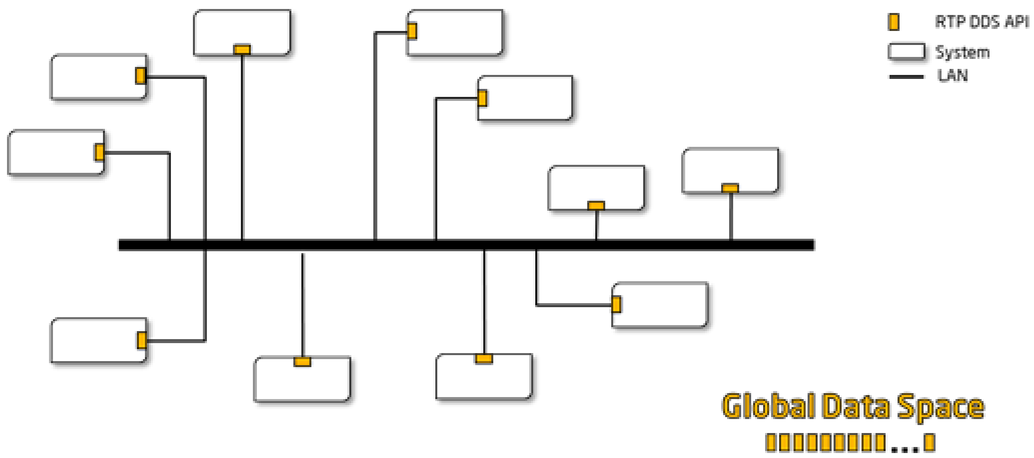
3.5.1.4. iSPEED Real Time Platform

The iSPEED Real Time Platform plays an important role in Wikinger and East Anglia I, bridging the gap between smart grid components and high level tools (such as analytics and O&M systems) which are needed to implement the use cases.

The Real Time platform communication paradigm used in ROMEO is the DDS Field Message Bus: a real time acquisition and processing platform based on the Publish/Subscribe data-distribution paradigm which supports publish/subscribe and request/reply real-time communication. It is built over an implementation of the Data Distribution Service (DDS) standard for real-time middleware from the Object Management Group (OMG). DDS aims to enable scalable, real-time, high-performance and interoperable data exchanges between actors. DDS addresses the needs of applications of processing huge volume of information that is going to be generated and distributed by the different actors involved. This one-to-many communication provides anonymous, decoupled, and asynchronous communication between the publisher and its subscribers.

It is important to remark that the DDS specification requires the implementation of a Global Data Space (GDS) to be fully distributed to avoid point of failures and single point of bottleneck. This GDS will be made from all the local object caches of the systems that are sharing information through the Real Time Platform: publishers and subscriber

Whether new actors appear in the communication or if more information needs to be exchanged, iSPEED facilitates the integration of both requirements without hardly affecting the ecosystem of applications that is working. Thanks to the use of an information model known by all participating systems/applications and services, it is not necessary to define new interfaces or adapt existing ones. This greatly provides a flexible and robust communications ecosystem. For example, the deployment of Node#1 in EA1 demonstrator occurred at the end of the ROMEO project, when Wikinger demonstrator information data was already being acquired and distributed, and this new actor and the information it acquired did not affect the rest of the connected systems at any time.



Being a distributed middleware based on the Publish/Subscribe paradigm, a single data publication is required to inform all subscribers, which significantly reduces information traffic between systems. Along these lines, at ROMEO we have been able to demonstrate how the data sent from the Node#1 Gateway or from a SCADA acquisition application, such as BABEL, have been shared and distributed among the different systems – as the IBM Cloud or embedded algorithms- using the same communication interface without having to adapt or change with new actors or new wind turbine information.

3.6. Centralised O&M Management Platform

3.6.1. HARVEST

The acquisition of information requires a uniform structuring and unambiguous identification of the individual plant components that is applicable regardless of technical asset design. Different degrees of information detail are required for the various tasks involved in asset management: for example, controlling tasks require information relating to the wind power plant as a whole. For planning and procurement, on the other hand it must be possible to provide information right down to component level. Within the O&M platform HARVEST these different information hierarchies is clearly structured and unambiguously addressed.

To provide such a uniform communications basis for the monitoring and control of wind farms the O&M platform provides a powerful asset management tool. It defines wind power plant specific information with wind power plant components in a manufacturer-independent environment. In detail this wind power plant specific information describes the crucial and common structure, scope and configuration information. The information is hierarchically organised and covers for example common information found in the rotor, generator, converter, grid connection and the like. The information may be simple data (including timestamp and quality) and configuration values or more comprehensive attributes and descriptive information, for example engineering unit, scale, description, reference, statistical or historical information.

The O&M platform HARVEST can merge the existing data architectures of different wind turbine vendors. In addition to the ability to monitor wind farm field data on a dashboard, the system enables condition-based maintenance (CBM) and predictive maintenance (PdM) for individual turbine parts by combining various information (events, time-based sensor readings, external data sources), performing powerful analytics and generating specific actionable advisory information that can be fed in to asset management and directly supports the maintenance process. The O&M management platform includes also but not limited to:

- Work order generation, prioritization, and tracking by equipment/component.
- Historical tracking of all work orders generated which become sortable by equipment, date, person responding, etc.
- Online visualization tool, for handling of large data sets
- Analytics function library for implementation of project specific algorithms for data analytics, KPI calculation and prognostics.
- Integration of UE knowledge base for formalized storage of expert knowledge
- Ability to drive business relevant processes, asset management organization and advisory information.
- Built-in intelligence to direct support business processes by means of analysing and combining multiple information and generating actionable recommendations.

The ROMEO project has introduced the following innovations in HARVEST:

1) Advanced IT infrastructure and data security approach: A fully scalable, highly secure data centre was used as the IaaS (Infrastructure as a Service) platform for the O&M Information Management System. This platform is physically located in the RRZ data centre in Graz/Austria and was initially configured to ensure that the O&M Management System is accessible by stakeholders from all wind farm operators and partners. The RRZ infrastructure provider ensured the highest level of system and data security, and sufficient resources were made available to guarantee that complex calculations, as well as large-scale data transfer can be properly supported. To preserve the data confidentiality and security, the whole system platform was hosted at a certified data centre and thereby maximum data security and system availability was expected. Communications between client and cloud service/system takes place solely via secure channel (HTTPS), furthermore access to system/database was restricted only to authorized personnel like system/database administrators.
2) New interface connected with data analytics ecosystems based on IBM Cloud and advanced functionalities for WF operators: A new interface located in the Utility Application End User Layer of the data acquisition ecosystem was created to connect IBM Cloud and HARVEST. It provided the relevant inputs for the O&M Management Tool. These inputs included the results from the physical and statistical analytics models as well as SCADA Data from the demonstrator wind farms, such as turbine alarms and relevant time series data. The developed interface specification and data exchange protocol was also intended to serve as a standard procedure for the data exchange between the IBM Cloud and other external tools, such as Domina G. The design of this interface allowed a full integration within a central Data Acquisition and Analytics Ecosystem for maximum benefit from underlying computing resources. The smooth connection among both IT solutions ensured the efficient execution of the following advanced functionalities: KPI calculation, visualisation & monitoring, and event-based reasoning.
3) New algorithms to drive business relevant processes: and asset management tools HARVEST acquired the ability to drive business relevant processes, asset management organization and

advisory information. The user- friendly arrangement allowed various users working in several environments efficiently interacting with the system, extracting information, and providing feedback. The acquisition of information required a uniform structuring and unambiguous identification of individual plant components that is applicable regardless of country or turbine type. The project allowed establishing solid synergies and value-creation with digital twins and incorporating a novel data management structure. HARVEST incorporated the following post-processing, information extraction and advisory generation novelties: 1) Flexible state & event processing system, 2) Integration with diagnostic and prognostic algorithms, 3) KPI functionalities, 4) Recommendations and advisory statement system

3.6.2. RamView360

RamView360 is a web-based visualising tool developed by Ramboll to present the digital twin model of the asset. It can be easily operated through a web-browser on a computer or mobile device. Due to its low bandwidth data requirement, the BIM model can swiftly load and operate very fast compared to traditional desktop applications. RamView360 is also compatible with VR glasses or VR cardboard setup by placing a mobile phone into a frame made of cardboard material. The displayed information alongside the digital twin model can be configured as per the customers' requirements. The tool can also communicate data through software API connection with Ramboll's internal web interface or any external software applications.

RamView360 provides a 360-degree view from a specific viewing location in a 3D environment. It allows a wide range of functions to be visualised in the model, e.g., BIM visualiser, CFD simulations, CAD models and point cloud models generated from LiDAR scanning. This is achieved by utilising 360-degree images from detailed 3D modelling software (such as AutoCAD or Solidworks) or measurement data (such as point-cloud datasets from a LiDAR scanner). RamView360 uses the BIM method to represent the 3D model with overlaid technical information like component's RDS-PP code, incident metrics such as mean time between failures (MTBF) and mean time to repair (MTTR) , O&M manuals, HSE guideline files, weather data, water depth or temperature measured by sensors. A screenshot of the RamView360 dashboard panel with a wind turbine model is shown in Figure 38.

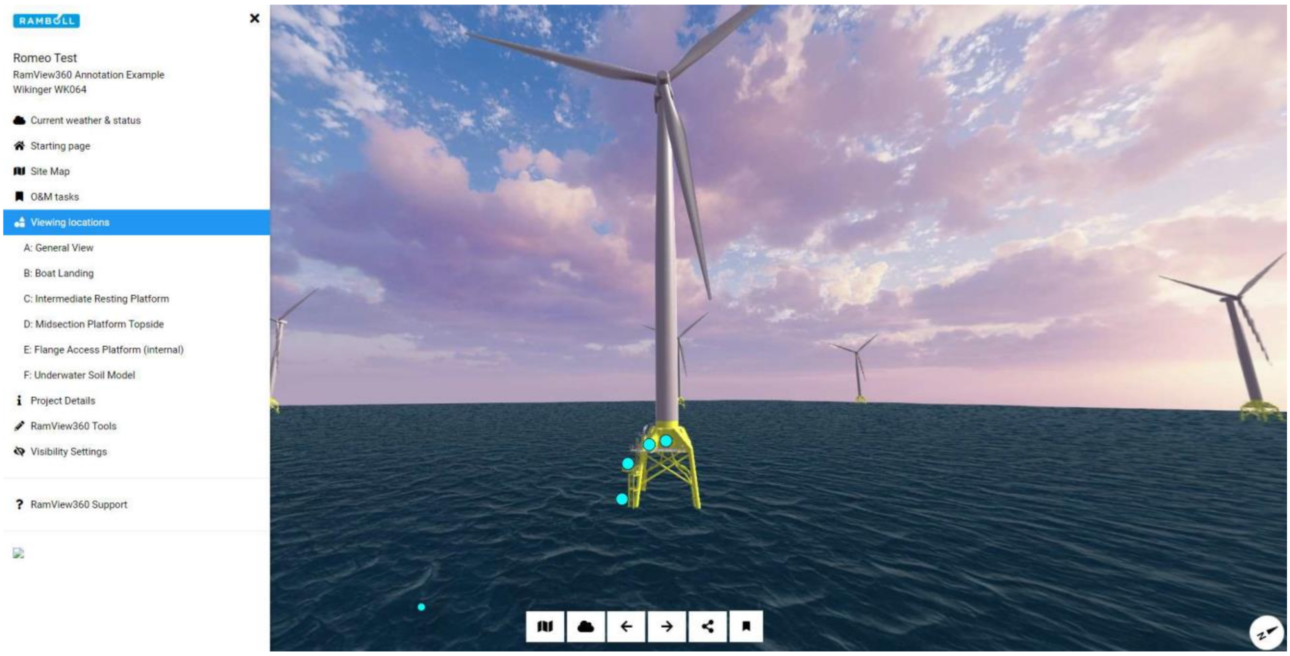


Figure 38 RamView360 dashboard panel

In context of offshore wind farms, Ramboll focusses on using this visualisation tool for the effective communication during the entire life cycle of wind farms. The Wikinger Wind Farm was chosen as a proof-of-concept site for the development of a 3D digital twin model. The wind turbine and foundation structure CAD model was transformed into the 3D VR model via virtual reality software Unity 3D [5] and 360° images were extracted to create the BIM model. As final step, annotation points were mapped into the 3D environment to present the asset information, O&M tasks, documents, and sensor data.

The RamView360 tool was also linked with the Uptime Solutions Information Management Platform developed by Uptime, to map the O&M task information into the BIM 3D model of the wind turbine. This proof-of-concept example shows the effective communication between different stakeholders of the wind farm through advanced visualisation technology. The model leads to improvements in communication, transparency, HSE standards on site, workflow optimisation, and cost optimisation.

3.7. Impact Assessment Model

The impact assessment tool that we have developed as part of the project addresses a number of limitations that have been identified, following a detailed review literature and market review. These account for (i) modularity of the solution allowing for appropriate tools/models to be included in the analysis, (ii) all phases of the tool to be modelled in adequate fidelity to allow for evaluation of the impact of different design conditions, (iii) operation and maintenance (O&M) costs should be calculated in detail and utilising latest reliability data through appropriate engineering models, (iv) uncertainties of key variables should be considered in a systematic way, assigning confidence levels on the expressions of estimated KPIs, and (v) the environmental impact throughout the service life of the asset should be assessed based on modern unit emissions databases.
The structure of the tool can be found in Figure 1.

The tool has been successfully implemented to allow for a flexible input of values and following appropriate analysis returns a number of valuable KPIs, including the levelized cost of energy, net present value, internal rate of return, as well as detailed cost breakdown per phase, sensitivity analysis of key simulation variables and life cycle cost profiles, among others. Specifically for the O&M module, users can get the total energy produced by wind farm, production based and time based availability, power production losses, power output per each turbine, breakdown of downtimes and O&M costs throughout the service life of the wind farm.
More details on the tool can be found in Deliverable D8.3: Documentation of impact assessment model.

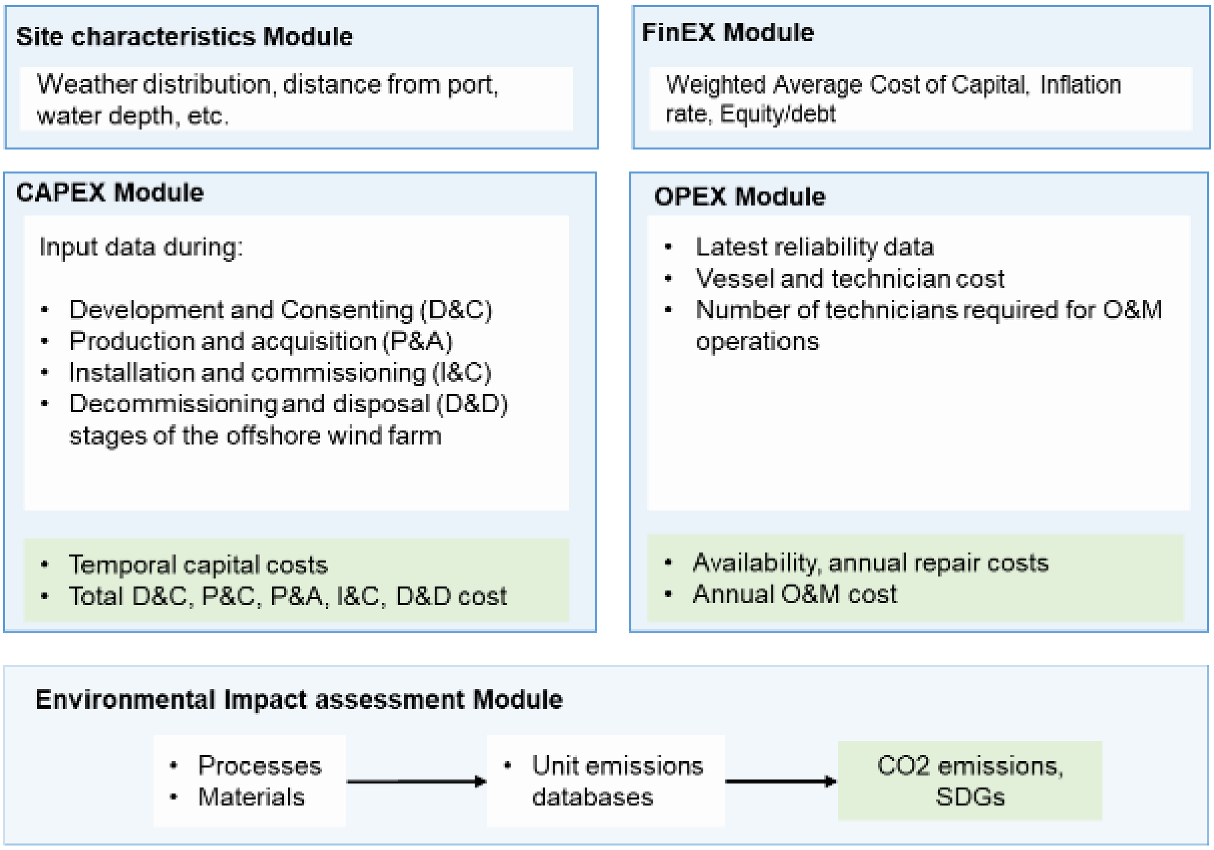


Figure 39: Methodological framework of impact assessment model

4. Conclusions

ROMEO is an EU Horizon 2020 project, developing Reliable O&M decision tools and strategies for high LCoE reduction on Offshore wind. Throughout this project, various innovations have been delivered, which are summarised in this document. The innovations cover a wide range of offshore wind applications; diagnosis and prognosis solutions (Section 3.2), failure mode models (Section 3.3), digital twins for asset management (Section 3.4), data acquisition ecosystem (Section 3.5), centralised O&M management (section 3.6). The innovations contribute to reduced costs and improved O&M of offshore wind.

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