D2.1

Failure mode diagnosis/prognosis orientations

ROMEO

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2.1	2019-05-27	Increase of the resolution of the pictures.

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Table 1. List of abbreviations.

Abbreviation	Description
AD5	Adwen 5MW wind turbine
CMS	Condition monitoring system
DC	Direct current
FE	Finite element (method)
FMECA	Failure mode and effects and criticality analysis
IGBT	Integrated gate bipolar transistor
IGCT	Integrated gate commutated thyristors
LCOE	Levelised cost of energy
ML	Machine learning
O&M	Operation and maintenance
PM	Permanent Magnet
ROMEO	Reliable OM decision tools and strategies for high LCoE reduction of Offshore wind
SCADA	Supervision control and data acquisition
WP	Work package

List of definitions

Table 2. List of definitions.

Definition	Description
Assembly Level	Assembly refers here to the resulting system from joining components and subcomponents to make a complete product and perform a specific function. Only high-level assemblies are considered in this document, and not very specific subcomponents). This way, all the failure modes targeted within ROMEO are covered.
Corrective Action	A corrective action is a maintenance task performed to identify and rectify a failure or malfunction so that the affected system can be restored to its original condition. Corrective actions can also include new documented designs to eliminate the cause of a failure or design deficiency.
Failure Cause	The physical or chemical processes, design defects, quality defects, part misapplication or other processes which are the basic reason for a failure to occur or which can initiate the physical process by which deterioration proceeds to failure.
Failure Mode	The failure mode is the way a failure occurs and develops in the system, which is directly related the way it can be observed and its impact on equipment operation.
False Positive	A False Positive is an error in which a detection/diagnosis model mistakenly indicates the presence of a failure, when in reality the system is healthy.
Life Cycle Cost (LCC)	Life Cycle Cost is the cost of running the equipment through all its operating life until decommissioning. It includes the acquisition cost, research and development, testing, manufacturing, investment costs, as well as utilization cost, maintenance support and personnel, spare parts, loss of production, transportation, tooling, etc.
Machine Learning or Machine Learning Process	Machine learning is a subfield of artificial intelligence, consisting in the scientific study of algorithms and statistical models that learn from and make decisions and predictions based on data.
Month	Month of the Project ROMEO, starting from June 2017 (M1)
ROMEO	ROMEO is a project dedicated to the design of O&M tools aiming at reducing the costs of operating offshore wind farms, and hence the LCOE of offshore wind.
Pre-ROMEO State-of-the-Art	Within ROMEO WP1, several FMECAs were conducted to identify critical failure modes affecting the wind turbines included in the project. Several partners from the Consortium, namely Bachmann, EDF, Siemens Gamesa, Adwen and Laulagun, have identified the available technologies for the diagnosis and prognosis of these critical failure modes, based

Definition	Description
	on literature review and internal assessments. As several shortcomings have been observed, the project aims at overcoming them to build new effective and exploitable diagnosis and prognosis solutions.
Proof of Concept	A Proof of Concept is the exploration of a method beyond the conceptual phase, in order to demonstrate the feasibility of its working principle. Proof of Concept is usually deployed in an early phase of an engineering design.
Technology Development	A Technology Development is a technical innovation representing progressive or radical advances in the engineering field. Technology Developments are usually developed by the Research, Development and Innovation departments from engineering companies to gain a competitive advantage for the exploitation of their products.
Wind Turbine	A Wind Turbine is a machine that converts the captured kinetic energy from the wind into electricity.

1. Executive Summary and State-of-the-Art

1.1. Executive Summary

This document covers part of the work conducted within ROMEO WP2 - coordinated by Siemens Gamesa -, more particularly the public deliverable D2.1, entitled “*Failure mode diagnosis/prognosis orientations”.* The main objective of WP2 is to develop diagnosis and prognosis solutions for new designs and arrangements. This is aligned with the general scope of ROMEO of anticipating failures in order to reduce O&M costs.

This report describes the different efforts for the implementation of the developed solutions for the diagnosis and prognosis of the targeted failure modes, into new designs. This is an enabler for the participating partners to exploit or port each of the designs into their products.

Within WP2, the development of some of these new solutions is performed by means of experiments at test bench level, intended to mimic real failure development and symptoms. Other developments are directly based on the analysis of data from in-service wind turbine. The data generated or selected in WP2 will also be useful in other WPs, such as WP3. Indeed, cost-effective solutions for the diagnosis and prognosis of the targeted failure modes are being built within WP3, although these are based on readily available data and not on new designs. As the success of WP3 relies on the use of data representative of both healthy and faulty behaviour, data from WP2 could be used to complete the necessary data requirements. Some other interactions with the rest of the project are summarised in Figure 1 and Table 3.

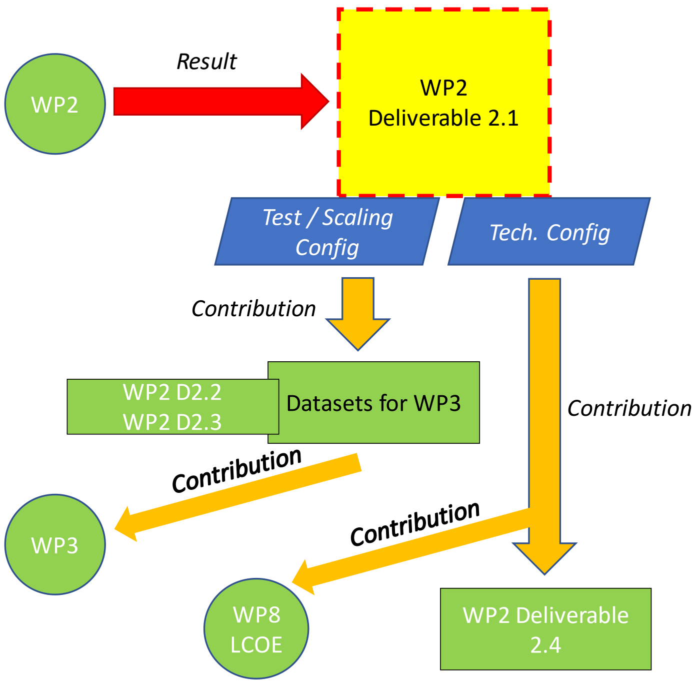


Figure 1. Map of interactions, inputs, outputs to other work packages and deliverables.

Table 3. Summary of interactions of Deliverable222.1 with other work packages and deliverables.

Type of interaction	Target	Summary of the interaction
Input	WP2 (Task 2.3 Drive train failure modes diagnosis/prognosis, Task 2.4 Blade bearing failure modes diagnosis/prognosis , Task 2.5 Electrical drive train diagnosis/prognosis)	Input from the Technical Developments together with the test and scaling configurations.
Output	Test/scaling configuration	The test/scaling configuration aids the Technology Configuration and at the same time it produces additional datasets to be used in WP3.
Output	Technology Configuration for Diagnosis/Prognosis	Every new Technology Configuration may be ported to the different products or it can be directly exploited.

This document is organised as follows. Sections 1.2, 1.3, 1.4 and 1.5 describe the current State-of-the-Art of the diagnosis and prognosis of failure modes affecting the different technologies studied within ROMEO; a summary is also provided in Section 1.6. Section 2 presents in detail the diagnosis and prognosis orientations within WP2 for the three main assemblies. The mechanical drive train is covered in section 2.3, while sections 2.4 and 2.5 are for the blade bearing and the electrical drive train respectively. Section 3 provides the conclusions and references can be found in Section 4.

On WP1, several failure modes were identified as part of the FMECA process (Deliverables 1.2 and 1.3). The equipment and the failure modes with the highest criticality was selected. Together with the feasibility to develop diagnosis and prognosis techniques and the technological support of at least two partners, several failure modes were selected as candidates for the development of diagnosis and prognosis orientations in WP2.

1.2. Current State-of-the-Art and innovative targets

As mentioned, the main objective of WP2 is to develop diagnosis and prognosis solutions for new designs and arrangements. This WP targets specific failure modes affecting three main assemblies, namely the **mechanical drive train**, the **blade bearing** and the **electrical drive train**. These failure modes were selected based on their occurrence and criticality, but also on their current detectability and diagnosis possibilities. Within this WP, several activities are developed aiming at studying degradation patterns preceding failures, to be used in the development of new diagnosis and prognosis solutions.

The main innovation target of ROMEO WP2 is the aforementioned global objective, that involves several specific targets highlighted subsequently.

Concerning the development of failure diagnosis solutions, WP2 activities are not limited in terms of design of new CMS. As a result, new sensors, new configurations or new experiments to be conducted at test bench level can all be considered. This is an innovative initiative to build tailored diagnosis solutions for the selected failure modes, to overcome the current shortcomings from the State-of-the-Art techniques [1]–[4]. Additionally, the developed solutions aimed at being probabilistic, supporting the concept of risk-based maintenance [5], and portable to other wind turbine types, contributing to advance the knowledge in the wind energy sector.
As regards the failure prognosis solutions, the thorough study of degradation patterns related to the selected specific failure modes will allow the development of future damage modelling and therefore the prediction of functional failures with sufficient reaction time. The reader is reminded that failure prognosis solutions should indicate when a functional failure of the system is likely to happen, given its actual condition.
Finally, the data generated during test bench experiments, or selected from in-service wind turbines within WP2 will be re-used in WP3, as it may offer very useful representation of specific failure behaviour.
In general, WP2 will lead to an improvement of available CMS for offshore wind turbines, as well as of diagnosis and prognosis techniques. The integration of the developed solutions into the Maintenance Management System will ultimately lead to a significant improvement of the O&M activities for offshore wind farms.
The State-of-the-Art in failure diagnosis and prognosis for the three main assemblies (mechanical drive train, blade bearing and electrical drive train) is described in more detail in the following sections. It is important to mention that this document does not intent to provide a thorough literature review on the topic of wind turbine condition monitoring, failure diagnosis and prognosis; the interesting reader is referred to several research publications covering the topic with in-depth surveys [1]–[4]. In general, there is still a significant margin for improvement and none of the aforementioned innovation targets has been deployed further than in a Proof-of-Concept phase. Finally, focusing only on prognosis, to date, a real prognosis system has not yet appeared in either traditional or wind industries because of the difficulties of setting the requisite mathematical models, although a number of efforts have recently been made [6].
Summing up, the main innovation targets of ROMEO WP2 can be summarised as follows:

- To develop diagnosis of failures showing degradation before failure;
- Prognosis of failures with sufficient reaction time (with error margin);
- Re-using data for the mixed approaches in WP3 (physical and data driven modules);
- Improvement of CMSs and diagnosis techniques integration to the Maintenance Management System and improvement of the O&M activities.

1.3. Mechanical Drive Train CMS State-of-the-Art (ROMEO Task 2.3 related)

The current available commercial solutions for monitoring the condition of the mechanical drive train are mainly based on classical approaches for rotating machinery, mainly consisting in vibration analysis [7]–[11]. These solutions rely on the installation of several sensors (mainly accelerometers and tachometers) in the different axes and components that send the vibration data into a centralized system. This data is later analysed by vibration specialists using dedicated software. Although vibration analysis techniques are effective for the diagnosis of some failure modes affecting gears and bearings, some other failure modes are neither covered nor the level of damage is assessed or classified. Furthermore, there is still a lot of uncertainty surrounding the diagnosis since it partially lies in human interpretation.

Task 2.3 within ROMEO WP2 will improve the data communication and the usage of the available vibration sensors for specific failure modes and damage assessment and classification. Also, Task 2.3 also envisions the integration of the CMS as part of the drive train, so that it will not be an add-on anymore. This will enable the exploration of new monitoring possibilities, new sensor arrangements as well as the diagnosis and prognosis of additional failure modes, uncovered by currently available systems.

1.4. Blade Bearing CMS State-of-the-Art (ROMEO Task 2.4 related)

At present, no commercial blade bearing CMS is available for offshore wind turbines. An in-depth review of academic and commercial literature founded only limited commercial solutions for small onshore wind turbines only covering wear monitoring [12]; the few founded academic studies are still limited to experimental data [13]–[16]. The State-of-the-Art of blade bearing CMS is clearly at a very early stage, with highly significant margins for improvement.
As concerns the wind turbines from the Siemens Gamesa group, no specific deployment for a blade bearing monitoring solution available at the moment. This is not only of great importance at a company level, but also at the whole European offshore wind industry level: at the end of 2018, Siemens Gamesa had the most offshore wind turbines in Europe with 69% of the total installed capacity. Some internal initiatives have been conducted though, mainly based on measurements performed in the pitch system roller bearings at a factory level. In these experiments, the ball pass frequency and the rotation of the inner ring were measured in order to calculate the differences between the actual and the theoretical contact angle. Nevertheless, these experiments were neither validated nor extended for diagnosis purposes. Additionally, Siemens Gamesa blade bearing suppliers have been contacted on this matter with no success.
Some of the most relevant academic studies have addressed the problem on the real-time estimation of blade bearing friction under varying conditions, and its evolution due to ageing or damage over time. As discussed in [16], knowing the material properties and a damage model, monitoring of the friction can be used for building effective blade bearing CMS. Task 2.4 will start out from this premise to produce diagnosis and prognosis solutions for blade bearings for the first time.

1.5. Electrical Drive train CMS State-of-the-Art (ROMEO Task 2.5 related)

Monitoring solutions for the wind turbine electrical drive train are still very limited, while these components are also major contributors to failure occurrence and downtime. A few recently new studies can be found suggesting solutions for the diagnosis of electrical generators, converters and transformers. While the diagnosis of generators has been slightly more explored, most of the studies focus on doubly-fed induction generators (DFIG) [17], [18], that are unfortunately not the preferred technology in the offshore environment. Conversely, permanent magnet generators are increasingly found offshore. Furthermore, as concerns power electronics, the CMS State-of-the-Art is even at earlier stages mainly due to the rapid evolution of failure modes affecting these components. Some diagnosis examples can be found for the converter [19], [20] and the transformer [21], and a German

patent seems to provide the basis for developing a prognosis solution for power converters based on insulated gate bipolar transistor (IGBT) technology [22].
As one can see, the problem of the diagnosis and prognosis of failure modes affecting the electrical drive train is still at a very early stage and offers obvious possibilities for improvement. ROMEO aims at overcoming this lack of solutions by developing new diagnosis and prognosis techniques.

1.6. State-of-the-art (Conclusion)

As presented in detail in the previous sections, ROMEO WP2 aims at covering the industry gaps in terms of failure diagnosis and prognosis at the corresponding level for the different assemblies.
The different technologies studied, the failure modes covered and their corresponding State-of-the-Art in terms of CMS, diagnosis and prognosis are all summarised in Table 4.

Table 4. Summary of the State-of-the-Art.

Technology	**Subtask**	**Failure Modes Covered**	**Pre-ROMEO State-of-the-Art***
Drive train – CMSSTD	Task 2.3	Gearbox failures (all) Main bearing failures (all)	Proof-of-Concept following VDI 3834
Drive train – Imbalance	Task 2.3	Rotor & Drive train failures.	Proof-of-Concept
Drive train – Damage Class	Task 2.3	Main Bearing failures (all)	No Concept
Drive train – Displacement Sensors	Task 2.3	Main Bearing failures (all)	No Concept
Blade bearing CMS	Task 2.4	Raceway/Ball fatigue Raceway/Ball wear out	Technology Concept
Electrical drive train detection techniques	Task 2.5	Generator PM Generator Winding Transformer Winding Converter DC link Converter IGBTs	No Concept
Scaling Up Methodology	Task 2.5	Electrical Drive Train (all)	Technology Validated in a different environment.

2. Failure diagnosis/prognosis orientations

2.1. Aim

The high-level goal of WP2 regarding Technology Development of the diagnosis/prognosis orientations allowing the reduction of O&M costs (OPEX), and so then the LCoE, in exchange for an increase of the design efforts (reflected on the CAPEX). A scheme of the interaction between the technology development tools (design tools) and the OPEX and CAPEX is illustrated in Figure 2.

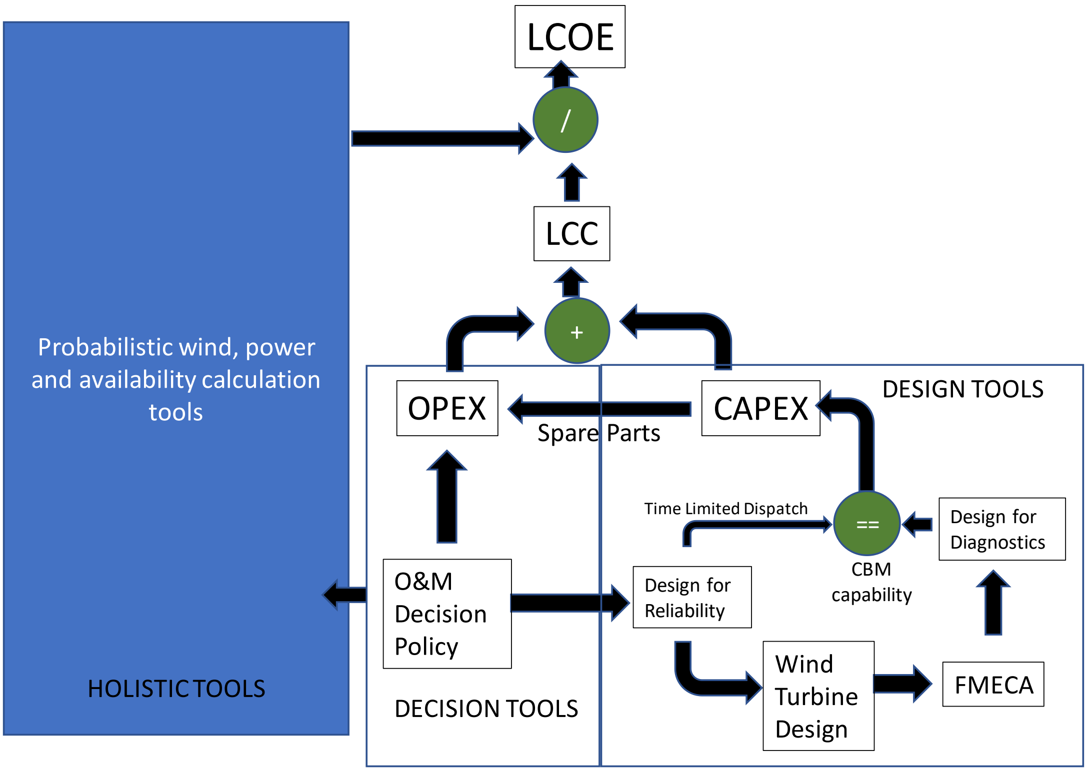


Figure 2. Scheme of Technology Development tools (Design Tools) influence on CAPEX and OPEX impact on LCOE.

Among the aforementioned ROMEO WP2 innovation targets, this document seeks to fulfil more specifically the following goals:

- To describe the developed orientation for failure diagnosis and prognosis;
- To describe links between small scale and full-scale testing and Validation aids. This is an initial step for re-using data in WP3;
- To present a brochure of the Technology Developments achieved enabling them to be deployed into a Maintenance Management System.

2.2. Wind Turbine manufacturer introduction

Siemens Gamesa acting as a backbone of the developments allows the partners to have access to the framework of a Wind Turbine manufacturer and will provide support in the portability cases thanks to these orientations.

At the same time, this facilitates individual exploitation of the results by each of the technological partners within Task 2.3, Task 2.4 and Task 2.5.

2.3. Drive Train (Main Bearing & Gearbox) diagnosis / prognosis orientation (Task 2.3)

2.3.1. Introduction (Task 2.3)

Bachmann is a provider of CMS products and services, with a proven experience of more than 20 years. Over 9,000 onshore and offshore wind power plants are already equipped or monitored by Bachmann Monitoring solutions, certified by Germanischer Lloyd. This experience and position prove their expertise in monitoring the mechanical drive train.

Within WP2 Bachmann focuses on failure modes which have a significant impact on the drive train. Based on the analysed approaches the cost of operating and maintaining each turbine can be reduced, thus decreasing the LCOE.

The approaches can be separated into online and offline analysis.

1. **Online analysis– Onsite**: Online analysis will be performed on the controller of the CMS within the turbine, so called edge computing. Figure 3 shows the different approaches, which have been analysed. An advantage of edge computing is that failure modes showing a short P-F interval (the time interval between the detection of the fault and the functional failure), can analysed in real time. The real time results can be passed to the wind turbine control system, so that the turbine can be either stopped or loads can be reduced (drive train, structure, blades).
   A real time approach is realized within CMSSTD 2.00, which can process the real time rms values provided by the CMS hardware. Information about high vibration levels or loads can then be directly provided to the control system of the wind turbine.
2. **Offline analysis - "mid and long term"**: Failure diagnosis and prognosis (gear box, main bearing). Failures and Damages within wind turbines usually develop over weeks and months. Each failure mode is showing typical patterns and changes, which will be integrated into different offline diagnosis approaches.

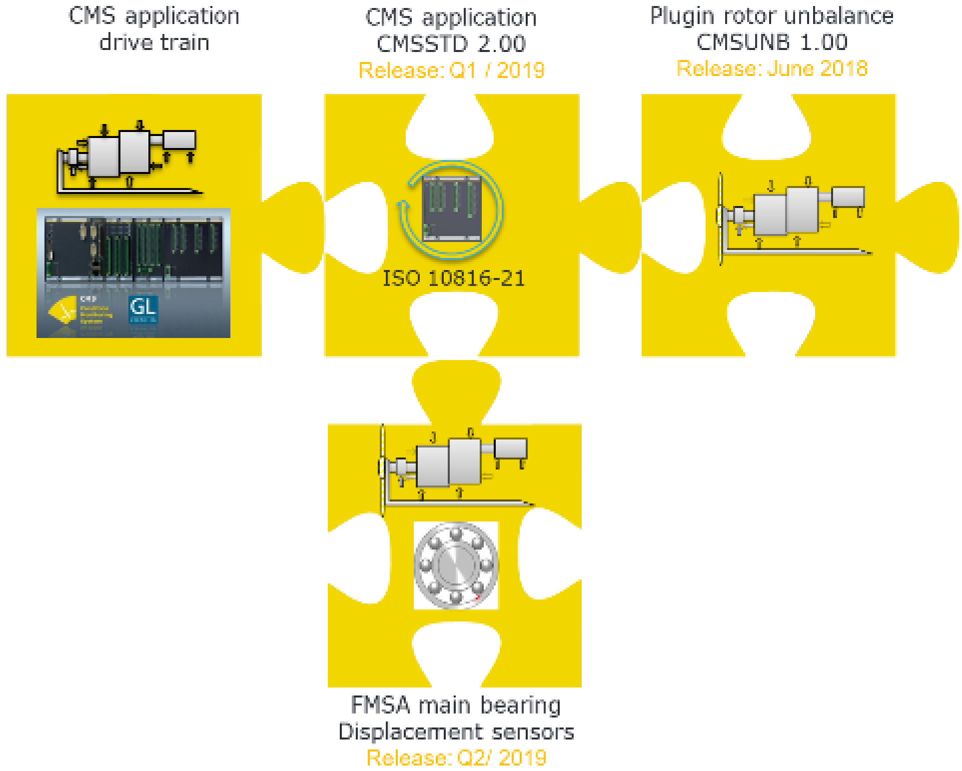


Figure 3. Overview of the different modules.

2.3.2. Online analysis CMSSTD 2.00 - RMS

2.3.2.1. Aim

Modern offshore turbines usually have higher rated power output compared to onshore turbines, which requires bigger components and results in a higher weight. Vibration of the components may be caused by events such as misalignment, aerodynamic imbalance or mass imbalance of the rotor. These vibrations cause dynamic loads, which may reduce lifetime of the components of a wind turbine.
In the field of vibration analysis for condition monitoring of rotating machinery, the Root Mean Square Amplitude (RMS) is the square root of the average of the squared values of the waveform from the raw vibration signals. This rms value is a very good measure for the energy within the vibration and can be used as an input for control systems to ensure a reliable and safe operation.

Within the ROMEO project the CMS Software module CMSSTD 2.00 was further developed and is now supporting the Condition Monitoring Hardware Module AIC214, which provides real time rms over configurable evaluation periods. The real time rms can be integrated into the turbine control in order to reduce loads on the drive train or for shutting down the turbine to prevent consequential damages. In addition, the info can be passed to a SCADA system, e.g. Wind Power SCADA from Bachmann (see Figure 4), that allow the users to assess the level of vibration of their drive trains.

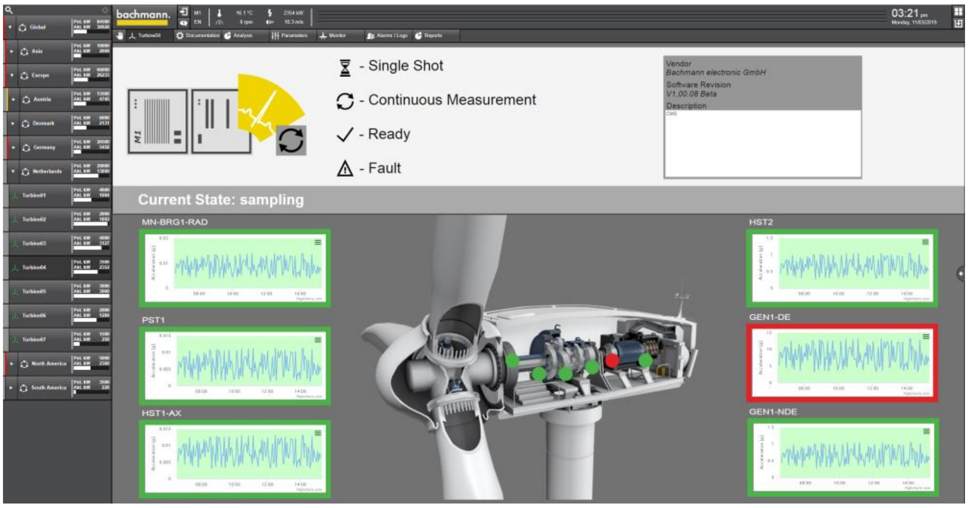


Figure 4. Bachmann Wind Power SCADA with integrated CMS.

2.3.2.2. Failure description

This system is able to detect failures related to the rotor, gearbox and main bearing in an advanced stage that may compromise the structural integrity of the wind turbine. The principle is to make effective detection of high levels of vibration as this may be an additional source of degradation of all the nearby elements in the nacelle and the tower.

The rms value in general is a good value for the energy content of a signal. Machine failures, which provide a significant contribution to the rms value can be detected. Examples for such failures are:

- Imbalance (of higher speed components);
- Misalignment of components, shafts;
- Bends;
- Looseness;
- Advanced damages.

Furthermore, the standardized parameters and thresholds can be used to:

- reduce dynamic loads on the wind turbine;
- detect fast progressing failure modes with a short P-F interval or component breakages (leading to a trip).

Figure 5 shows a sudden change of the condition. Usually the data will be transferred from the CMS to a central server, a vibration analyst will analyse the alarm condition and will create a report. For some failure modes this may take too long, so use of the real time calculated rms value within the turbine control can prevent consequential damages.

A high vibration level can either reduce the lifetime of other components or the component itself. Within the VDI3834 and ISO10816-21 evaluation bands for wind turbines have been defined. VDI 3834-1 provides limits for different components, which can be used for a permanent monitoring of the drive train and turbine.

The evaluation period within the module can be adjusted from 1s up to 10 minutes. A 10-minute evaluation period is required for most of the sensor positions at the main bearing and gearbox. As this is a quit long interval, an application on the controller can be used to calculate sliding RMS values with an update rate of 1s.

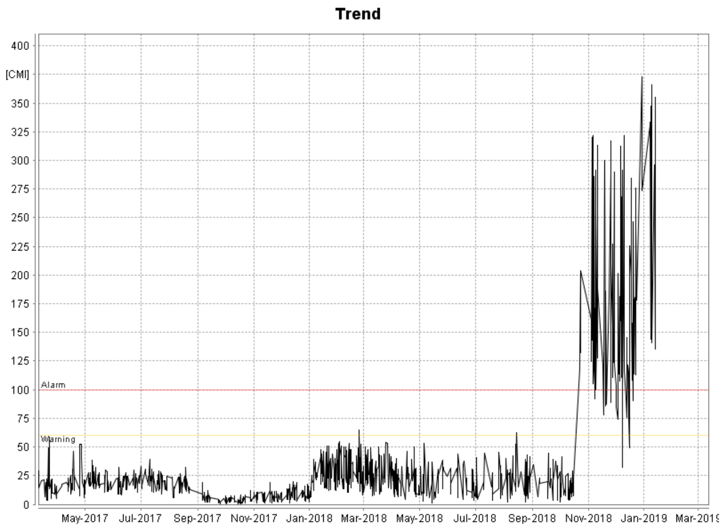


Figure 5. RMS Trend showing a sudden change.

2.3.2.3. System description

The M1 automation system's AIC modules offer a vibration monitoring solution that can be fully integrated with the control system. However, the CMS hardware alone will not help you to detect or prevent failure. This can only be achieved with the appropriate software to carry out the advanced signal processing and generate the appropriate characteristic values.
CMSSTD is the controller software which runs on the hardware system. CMSSTD supports system set-up through a browser-based interface used by the installers on site, carries out the advanced signal processing using our own order tracking algorithms to enhance the accuracy and repeatability of our results and also controls the storage and communication of the results locally and back to the central server.

2.3.2.4. Inputs / Outputs

Inputs for the module are all sensors, that are connected with the CMS module AIC214, as the VDI 3834-1 (ISO10816-21) will be used to assess the level of vibration. (e.g.: accelerometers).
The real time rms parameters for each sensor will be configured on the hardware module itself, providing the following parameters:

- Evaluation band: band pass filter according to VDI 3834-1, ISO 10816-21;
- Evaluation period: period for rms calculation;
- Limit Delay: alarm status is required to stay above the limit for the configured time in order to trigger an alarm.

The outputs are:

- A physical indicator pointing out the characteristic value of each sensor level of vibration according to the VDI 3834 / ISO10816-21.

The CMSSTD application can use the calculated parameters for trending within the WebLog and WebLog Expert application (see Figure 6). In addition, the CMSSTD application can be triggered in order to store the data in case of an alarm, the so-called *Event recording*. Data from an event will be read from the ring buffer of the hardware module.
The data can be used for a further analysis within the CMSSTD application for identifying the root cause of the failure and provide relevant data for the offline Failure Mode and Symptom Analysis (FMSA), which is in development within the offline diagnosis module. We intend to implement the methods for diagnosis developed within Romeo within our offline diagnosis module, which is in development.

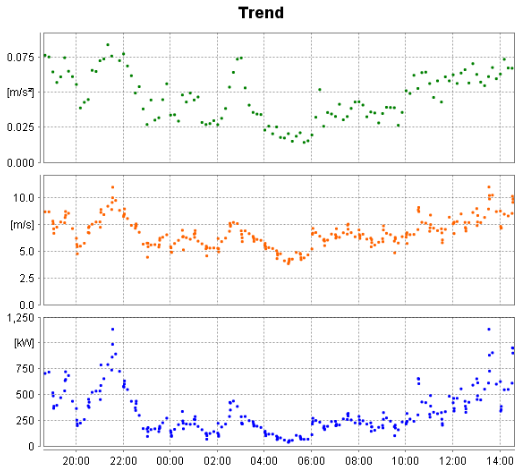


Figure 6. 10min values of vibration, wind speed and power output.

2.3.3. Model based unbalance calculation

2.3.3.1. Aim

Given the current focus on trying to reduce the Levelized Cost of Energy (LCOE) and wind turbines approaching or exceeding their 20-year design life, individual component wear caused by mechanical interaction has taken the limelight for the industry. A common culprit for turbines showing accelerated wear and premature failure within the drivetrain 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 calculations have been performed by experts. These calculations have required technicians to equip turbine blades with trial weights, start the turbine, take vibration readings, recalculate mass unbalance, adjust the weights accordingly, and repeat until the turbine is operating within tolerance limits. This process presents safety risks and leads to production loss. A study for 10 2MW onshore turbines [23] says that approx. 100.000 € have to be spent for measurements. It can be assumed that the costs for offshore turbines will be even higher.
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.

Online systems for rotor unbalance calculation can reduce safety risks and production loss, as well as provide a clear trend with greater sensitivity for balancing. As part of a 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.

By reducing the effects of a significant cause of wear for the turbine, the cost of operating each turbine will be reduced, thus decreasing the LCOE.

2.3.3.2. Failure description

As some unbalances may appear or may come from the manufacturing and assembly, regular checks of the status of the balancing of the turbine would be needed in order to ensure low vibrations due to mass unbalances.

That is lengthy and expensive, but the implications of an undetected unbalance are also severe: increased fatigue loads on the entire structure, including the tower and nacelle, as well as the drivetrain components. Providing a cost-effective estimate of the balance quality allows owners to target those wind turbines where balancing will make a significant improvement to the operational life.

2.3.3.3. System description

The model based approach is based on a finite element model (FE model) of the wind turbine and is based on the research from Ramlau and Niebsch [24], [25]. Within the ROMEO project Bachmann optimized the data pre-processing and implemented the algorithm.

In principle the movement based on a mass unbalance (mass m_i at radius r_i) can be described as follows:

$$\mathrm{u(t)} = r_i \frac{m_i}{m} \mathrm{V_u} \cos(\omega_0 t + \varphi)$$

with:

$$V_u(\eta) = \frac{\eta^2}{\sqrt{(1-\eta^2)^2 + (2D\eta)^2}}$$

$$\eta = \frac{\omega}{\omega_0}$$

where ω is the angular frequency of the rotor and $\omega_0 = 2\,\pi\, f_0$ is the 1st natural frequency of the tower. As shown in Figure 7 the amplitude increases when the rotational frequency approaches the resonant frequency of the tower / structure.

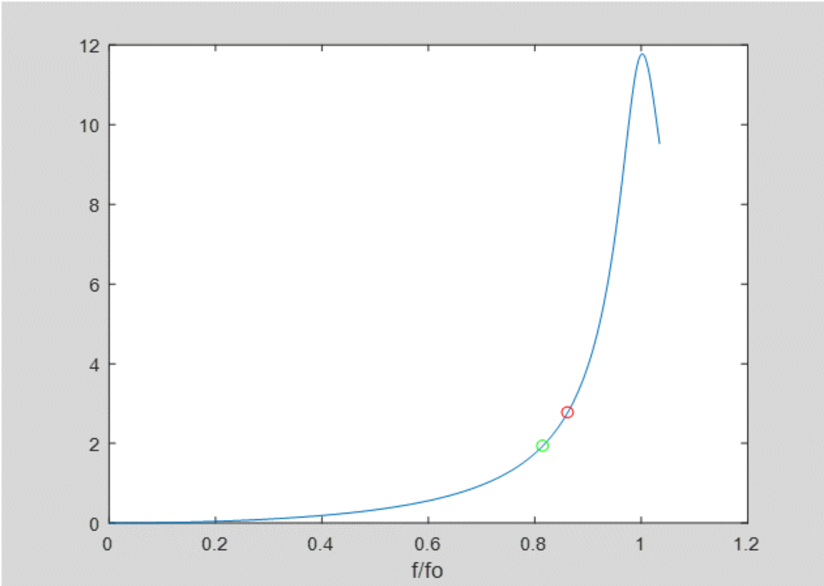


Figure 7. Resonance transmissibility V_{u}.

The load vector $\vec{p}$ of the mass unbalance and the displacement vector $\vec{u}$ is connected via the transfer matrix A:

$$\vec{\boldsymbol{u}} = A\,\vec{\boldsymbol{p}}$$

The transfer matrix can be estimated using the stiffness matrix *S* and the matrix of inertia *M*:

$$\mathrm{A} = (-M + \omega^{-2}S)^{-1}$$

The tower itself is modelled using a bending beam model, the elements are considered as hollow cylinders (Figure 8).

Figure 8. Simplified system with masses, kinematic parameters, elasticities and damping properties.

The FE model of the tower provides two matrices:

- Stiffness matrix S;
- Matrix of inertia M.

Based on the stiffness matrix and matrix of inertia the transfer matrix is calculated and the parameters are stored in configuration file (tower file).

Figure 9 shows the principle input and outputs of the software module. The CMS acquires acceleration data and speed reference data, usually from the high-speed shaft. Based on the 1p (rotational speed of the rotor) vibration amplitude, the speed reference (ω) and the configuration based on the FE model the unbalance will be reconstructed. As a result, the software module provides the mass unbalance.

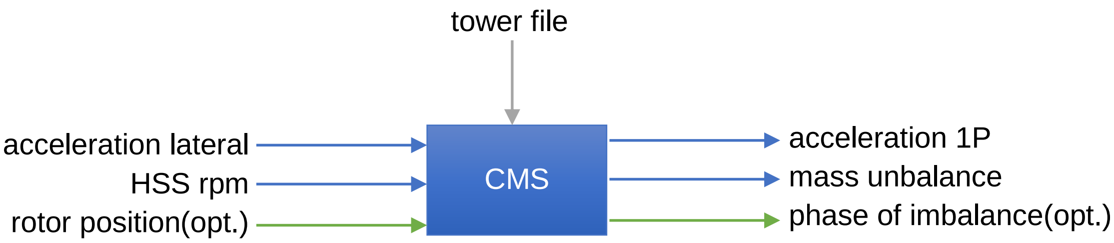


Figure 9. Mass unbalance: inputs and outputs (orange: optional) of the algorithm.

If an additional rotor position sensor is installed the module returns the position of the unbalance. Based on this information the position for the required balancing weights can be provided as well.

2.3.3.4. Inputs / Outputs

Inputs of the models are a subset of Bachmann 2D MEMS sensors on the centre of the nacelle, or additionally the rotor position sensor for increased precision. The outputs are:

- A physical indicator of the measure of the actual mechanical unbalance (in kgm);
- The trend of the unbalance measurement.

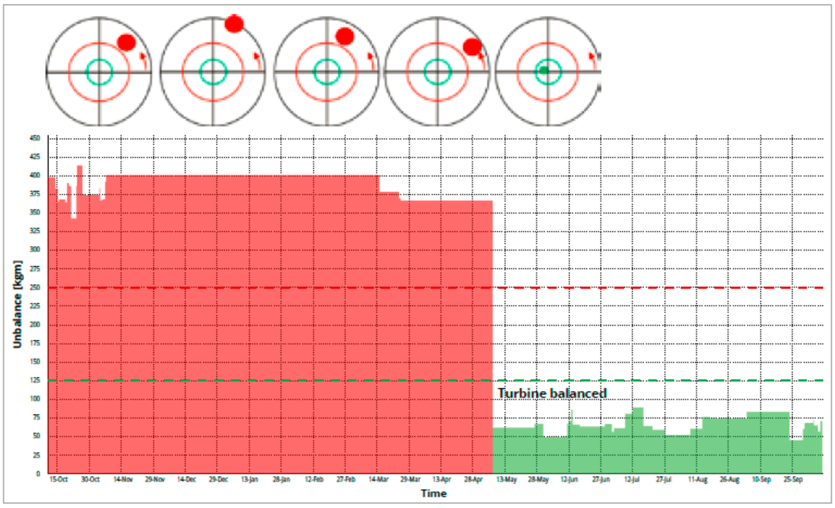


Figure 10. Algorithm output trend of the turbine balance.

2.3.4. Main bearing – use of new sensors

2.3.4.1. Aim

The system will aim to detect failures of the main bearing with the aid of a diverse technology. This will provide redundance and a better insight of the degradated phases of the failure.

2.3.4.2. Failure description

Fatigue crack progression on the outer race may damage the entire bearing and shall be detected before it starts affecting the surrounding equipment.

2.3.4.3. System description

This algorithm uses non-contacting displacement sensors that have been applied to measure the relative motion of housing and bearing elements.
The application of further sensors improves our understanding of the bearing dynamics in normal and abnormal operation.

Four sensors are installed, each of them spaced with a 90° angle, measure the distance between the hosing and the inner race of the main bearing.

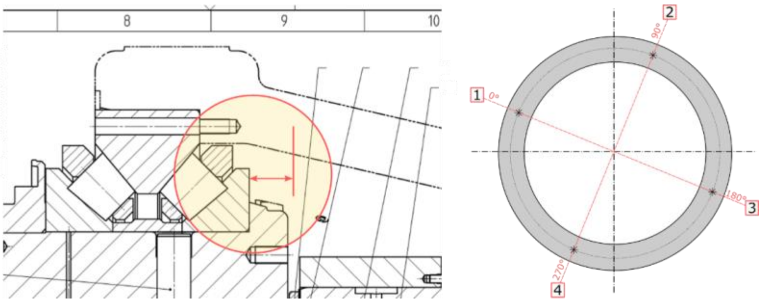


Figure 11. Positioning of the displacement sensors.

2.3.4.4. Inputs / Outputs

Inputs of the models are the displacement sensors over the main bearing. The outputs are:

- A physical indicator as the detection trend;
- A prognosis estimation based on these phases.

The displacement data of several main bearing damage cases and patterns can be used as a damage indicator in the condition monitoring process.

The results show that the displacement signals of 4 sensors contain information about the bearing condition but also about the position of a damage. To monitor the condition in time, damage indicators were defined, trended in time and included in the FMSA description for specific failure modes. A comparison of an acceleration and displacement trend is plotted in Figure 12. The displacement trend (red dots) shows a very similar performance to the acceleration trend (black line). The methodology has been applied on data of several historical damage cases. For each test a clear trend indicates the damaged raceway surface. For long term validation, the displacement trend was implemented in the online condition monitoring.

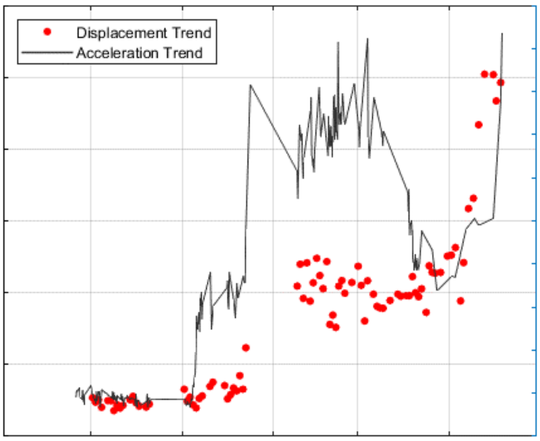


Figure 12. Comparison of acceleration and displacement trend.

2.3.5. Offline FMSA Diagnosis Module

2.3.5.1. Aim

The Failure Mode Symptom Analysis (FMSA) aims at characterising and defining attributes of a particular failure. It is the subsequent step of the FMECA and provides the foundation for the applied condition monitoring strategy. The presented methodology bases on both industry best practices and international standards. The main reference documents for this section are the *VDI 3832* [26] and the upcoming *ISO 16079-2* [27]. Following aims and requirements were defined for the diagnosis module:

- To statistically determine damage stages
- Robust and identical transducer setup
- The diagnosis method can be automated
- FMSA export function

2.3.5.2. Failure description

Symptoms
Symptoms describe system abnormalities, which can be linked to a specific failure mode. The first step in the FMSA process is to identify a suitable set of symptoms for failure diagnosis. These symptoms determine both hardware and software requirements for the CMS. Typical instrumentation for drive-train monitoring is listed in the following table.

Table 5. Drive-train monitoring: Instrumentation.

Sensor	Application
Proximity sensor	RPM data acquisition
Accelerometer	Early fault detection
Stress wave sensor	Early fault detection for lower speed items
Oil particle counter	Oil particle counter for advanced failures
Temperature sensor	Severe failure detection

The accelerometer is the transducer type most frequently used to monitor main failures types, such as bearing defects and gearbox faults. One symptom of a defect on a bearing raceway captured by an accelerometer is shown in Figure 13. The amplitude spectrum of a damaged bearing is characterised by distinct peaks. These peaks are associated with the ball passing frequency, which is the frequency at which rolling elements strike a surface defect on the raceway. The plot trends this frequency in time.

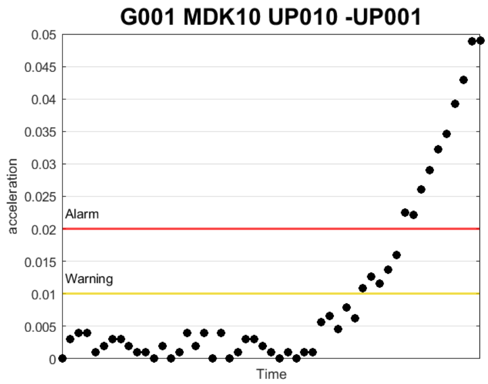


Figure 13. Characteristic frequency pattern for a bearing damage & trend.

Failures are usually characterised by multiple symptoms. The aim of the FMSA is to identify a group of characteristic values which: (a) guarantee a secure and robust diagnosis; (b) enable a damage classification and (c) derive prognosis data. Each characteristic value has a reference to the monitored component and its data source or sensor position. Both component and source are therefore labelled with a standardised RDS-PP code [28].

Algorithms

The first goal of the FMSA process is to determine a group of characteristic values for failure detection. However, symptoms and characteristic values alone do not give an indication of the severity of a damage. The following methodology introduces a classification system for damages. It is based on [26] and [29].

The severity of damage is important information within the predictive maintenance process. It is strongly linked to the urgency of repair and thus is a reference for O&M optimisation. In general, there are two main approaches to describe a damage classification system (see Figure 14). In the physical approach, the progression of a damage is reconstructed by means of kinematical and dynamical analysis. That process includes the symptom description and characteristic value definition explained above. In order to refine this description and introduce damage classes, characteristic values are (a) characterised individually and (b) logically combined. The latter includes characteristic value combination from different types of sensors (see Table 5), but also the combination of characteristic values derived from one sensor. The logical combination of multiple characteristic values increases the robustness of methodology. Furthermore, it enables an automated damage classification.

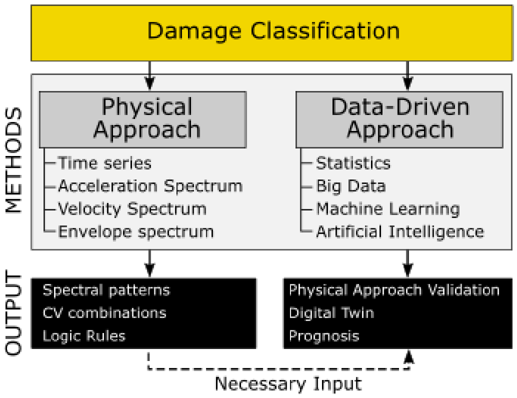
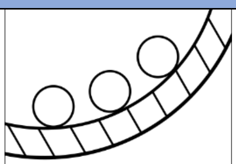
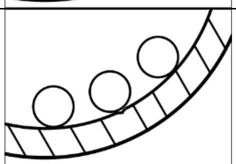
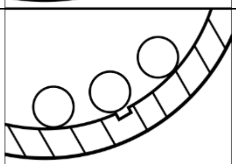
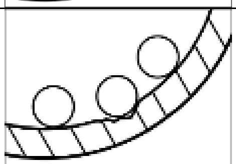
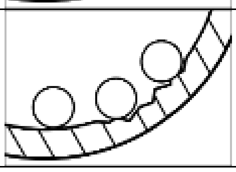


Figure 14. Damage classification approaches.

Acceleration data is suitable for both early fault detection and identification of more severe damage stages. Its time series data is post-processed to generate narrowband characteristic values based on acceleration, velocity and envelope spectra and broadband characteristic values such as the rms.

Table 6 summarises the damage classification of a bearing according to the standard [26]. The guideline introduces five damage stages, where damage stage 1 denotes a normal operation condition and stage 5 a very severe damage close to component breakdown. The last column of the table links the damage stage to a characteristic pattern of the ball passing frequency trend of the outer race (BPFO).

Table 6. Bearing damage: Severity classification according to VDI 3832. [26]

Stage		Description	BPFO trend pattern
1 Undamaged		No raceway damages.	Low amplitude trend. Absence of BPFO.
2 Incipient phase		Damage starts in form of pitting or subsurface cracks.	Increasing trend. BPFO above signal noise.
3 Growth phase		Damage size above 70% of the raceway width.	Increasing trend. Clear presence of BPFO due to impulse excitation
4 Transition phase		Tangential size below roller distance	Trend stabilisation or decrease. Damage progresses, but impulse character decreases due to material erosion.
5 Final phase		Tangential size above roller distance	Sudden trend increase. Two rollers fall into the damage zone (area is subject to rotor)

2.3.5.3. System description

The FMSA process is illustrated in Figure 15. Derived from the FMECA, the failure mode priority table lists the system's failure modes and its Monitoring Priority Number. It is the input of the FMSA, which generates characteristic fault indicators, a severity classification and prognosis data. These outputs are implemented in the condition monitoring architecture. By means of the created tools, the monitoring staff perform diagnostic and prognostic assessments. They communicate with the O&M staff via a customer portal. The communication is logged using a ticket system, which is also used to track the turbine's history. Moreover, CMS status information is provided through application programming interfaces (APIs), which can be integrated in O&M software tools.

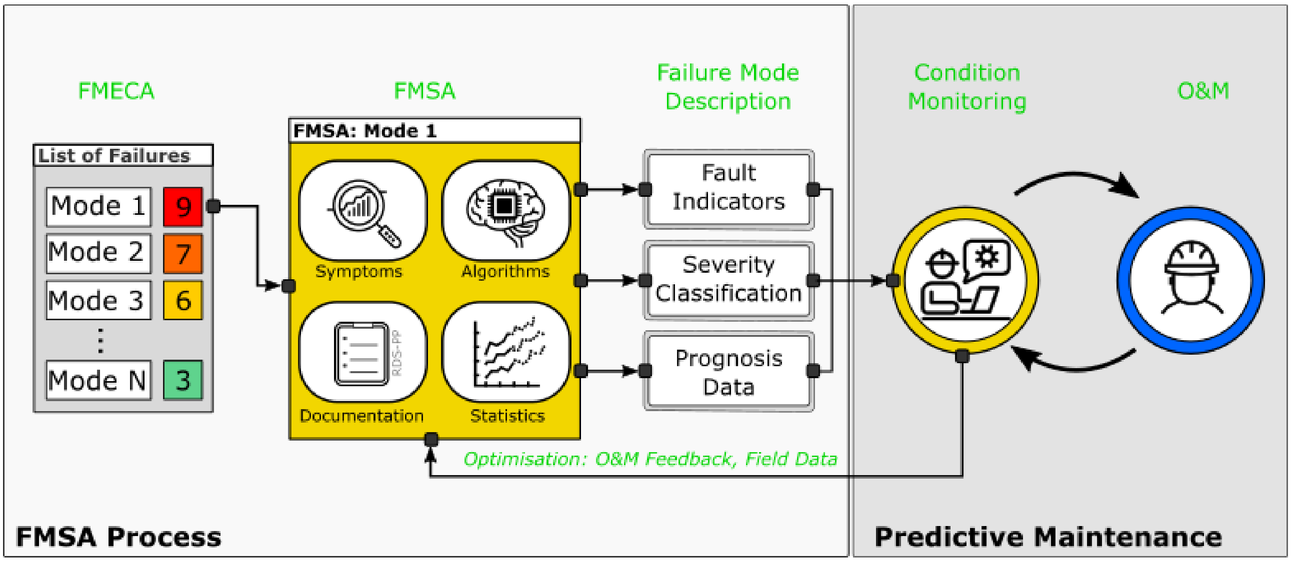


Figure 15. FMSA Process.

2.3.5.4. Inputs / Outputs

Inputs are the entire Bachmann CMS sensoric (accelerometers, mu-bridge, shaft speed, displacement sensors, etc). The outputs are:

- A physical indicator as the damage classes are a means to classify damages and are used as an indicator for their severity;
- A prognosis estimation based on these phases.

As the subsequent step of the FMECA, the FMSA refines the description of each failure mode. It generates a list of characteristic values, which are used for failure detection. Moreover, characteristic values are logically combined and statistically evaluated to introduce damage classes. They are used to estimate the severity of damage. The FMSA output provides experts with diagnostic information, which can be implemented in CMS tools. These tools generate automatic alarms, an automatic severity estimation and have additional functionalities for manual in-depth analysis.

The main output of this process is a clear diagnostic statement for the O&M process. This statement comprises the component (including RDS-PP code), its status (damage stage) and a recommended O&M action.

In current industry practice, diagnostic information is shared through ticket systems. A ticket system fulfils several requirements of the predictive maintenance process. It is a messaging tool for condition monitoring experts to contact O&M staff. In case of any system abnormality, a ticket is created. An attached report provides all necessary information to plan the O&M process. The O&M staff can give feedback, provide additional information such as endoscopy reports or upload documents such as the specification the exchanged component. After the component is repaired or replaced, the ticket is closed. It is kept as a record of the history of the turbine.

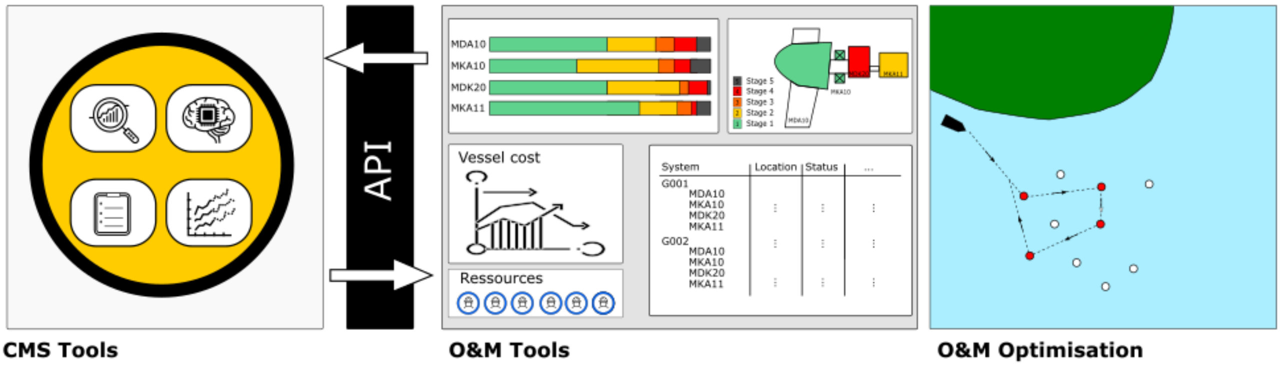


Figure 16. FMSA Output – CMS Tools.

Within ROMEO WP3, an API is created, which improves this process by providing an interface for O&M and asset management software. With the API, CMS status data can be implemented in service tools. Damage classification enables O&M engineers to estimate the urgency of a repair. Merging this information with further data like weather windows, vessel cost, component and resource availability, O&M tools become powerful instruments to plan and optimise maintenance activities and thus the operational cost of offshore wind farms.

2.4. Blade Bearing diagnosis / prognosis orientation (Task 2.4)

2.4.1. Introduction (Task 2.4)

There are many products and systems in the market that are focused on detection of different failure modes applicable to wind turbine equipment. However, for blade bearings there are no proper CMS in the market, as pointed out in section 1.4.

As a result, Laulagun is working on the development of physical systems to satisfy these possible needs. Special focus is being placed on the development of a methodology that will cover all these solutions to provide mitigation means against the most common failure modes. Based on these efforts, Siemens Gamesa will also port the learnt techniques into their products.

The development is being integrated as a new Condition Monitoring System.

2.4.2. Testing phase and data generation

Within ROMEO project, the work is focused on the development of modules for the major failure modes affecting blade bearings and that are compatible with the CMS that is already tested at the 8MW Windbox Test Bench facilities.

Windbox is located at the technological centre of IK4-Tekniker in Eibar, Spain. These facilities were conceived and designed in 2018 and have been built and mounted over that year.

The objective of this test bench was to generate data during the different operating conditions of the blade bearing. This allows the working team to gather an important amount of data from fatigue and ultimate tests performed on slow rotating bearings, sensorized for diagnosis purposes.
This is done while the data is being gathered and postprocessed. The final intention is to build diagnosis and prognosis methods that allow the detection of blade bearing failures with sufficient reaction time. The followed approach covers not only the structural side, but also ball and surface fatigue or wear problems.

The advantage of the WINDBOX test bench is that the whole rotor assembly of the wind turbine is mounted at the same time. This allows the test to be more realistic and representative of the relevant systemic conditions that will be encountered on the field. Actually, both the pitch system and the control system present at this test bench are working in the same way that for real in-service offshore wind turbines.

The test bench is composed by:

- A mechanical interface that allows the location of the blade bearings;
- A load application system, three for the fatigue loads (3 blade interfaces) and one for the test of extreme load (1 blade interface);
- Shear load compensation devices;
- Mechanical and electrical sensors;
- Full pitch system with cabinets, hydraulic system and cylinders;
- A control system.

Figure 17 presents a scheme of the test bench with main equipment.

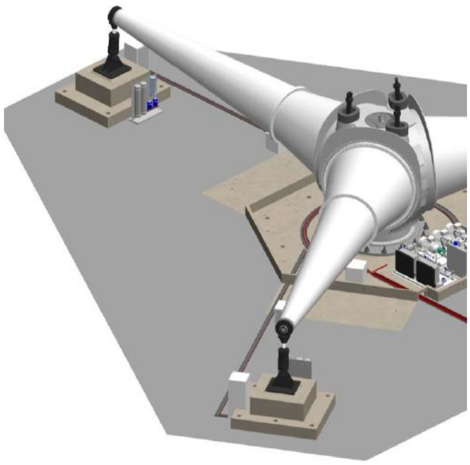


Figure 17. Windbox test scheme and main equipment.

In the WINDBOX test bench, the following tests can be conducted (without or with adaptations):

- Extreme load test;
- Static and dynamic model correlation (friction tests);
- Grease pressure test under load;
- Endurance tests;
- Configuration changes, assembly and disassembly.

The sensor arrangements allow the monitoring of the following parameters:

- Temperature, humidity and loads; (Ambient)
- Temperature, pressure, flow meters for the grease, high frequency and low frequency (MEM) accelerometers and displacement sensors; (Bearing)
- Strain gauges, displacement sensors, noise (acoustic pressure) and triaxial accelerometers; (Assembly Level, rotor hub)
- Pitch cylinders: Load cells, LVDT, pressure transducers,

The mechanical interface is a hub-laboratory interface able to withstand all the loads applied to the blade bearings. It is composed by three blade adaptors and can allocate three blade bearings. The main elements are the following:

- The load application system has been designed to cope with the extreme load tests, the static and dynamic model correlation, and the entire endurance tests. This is done with the use of tip application devices, shear load compensation devices. The maximum shear value is controlled via compensation device and an LVDT sensor and control system arrangement. The rest of the control variables are the loads applied from the cylinders (pressure, loads) and the displacements (LVDT) of any of the cylinders;
- A hydraulic power unit for the pitch cylinders;
- A hydraulic power unit for the load application units;
- The Laulagun CMS (See section 2.4.3);

The raw data acquisition system takes all the data channels related with vibration at a sampling rate of 500 Hz under a demand window and 0.5 Hz by default for acquisition of the RMS values.

2.4.3. CMS Blade bearing diagnosis / prognosis orientation

2.4.3.1. Aim

The objective of the project is to design and validate a solution for the most important failure modes affecting 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 for the development of these new capabilities.

2.4.3.2. Failure mode description

Two major failure modes affecting blade bearings need to be considered for the development of an effective CMS. The first one should focus on the Structural Health of the rings that compose the bearing, where the main concern lies in controlling the stresses that each of the rings is suffering. The second major failure mode is the Rolling Contact Fatigue of the bearing, where all the possible damage starts in the contact point between the rolling elements and raceways.

According to the research work performed by Laulagun, these two failure modes could be detected by the following approaches:

- Installing sensors directly in the blade bearing, in very specific positions;
- Eventually receiving information from the turbine (SCADA), especially with data related to the pitch angle and the loads that the turbine is suffering.

2.4.3.3. System description

A description of how the methodology works for the selected failure modes can be seen in Figure 18.

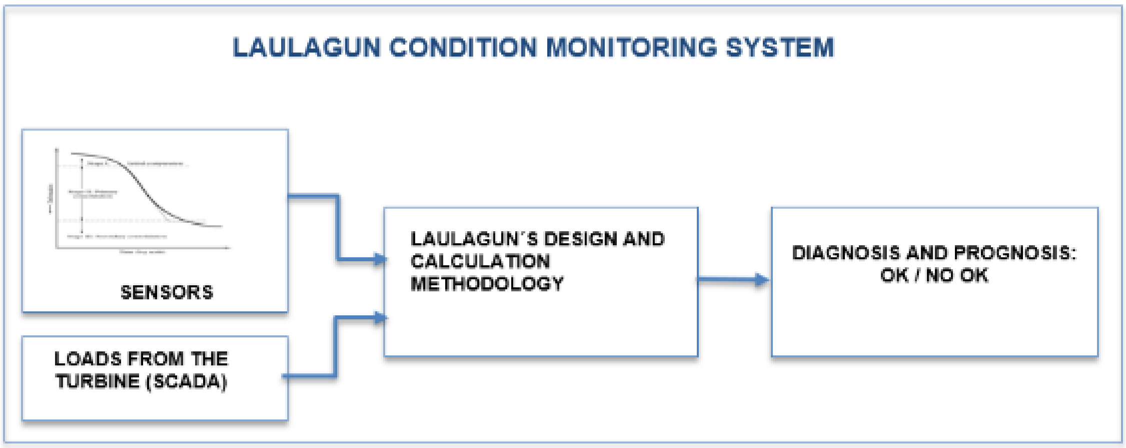


Figure 18. Laulagun Blade Bearing CMS.

As one can see, the methodology is fed by the information provided from the sensors and data monitored by the turbine (commonly known as SCADA). For the selected failure modes, the most common sensors are strain gauges and displacement sensors. Apart from the selection of the

sensors, what is also crucial is their location in the blade bearing, where best practice 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 on an online basis. This will allow to estimate the accumulated damage and therefore the condition of the bearing towards a particular failure mode (diagnosis) and its remaining useful life until the functional failure occurrence (prognosis).

The methodology will specifically focus on obtaining the loads in the areas 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.

Nevertheless, in case a connection with the SCADA is not possible, several options are available:

- To deduce the pitch angle from the signals of the strain gauges. It is possible to control how many rolling elements have passed from the raceway where the sensor is placed. It is something that never have been done, especially because a specific control must be develop to so and it is not an easy task;
- To install an additional sensor: The most common type of sensor would be an encoder. This would supposed to add more sensors to the control;
- To develop an approximate statistical criterion, to deduce how much the pitch is rotating.

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 fatigue damage that the bearing is suffering at each moment.

Finally, 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 new CMS 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.

2.4.3.3.1. Structural Health Monitoring of the rings

The severe load conditions which the blade bearings are subjected to, lead to the appearance and growth of cracks in their components ultimately leading to their fracture. We can differentiate the fracture due to overload, fatigue or thermodynamics. The most common different type of fractures described subsequently.

Forced or overload fracture: The overburden fracture generally occurs in areas of stress concentration, in which tensile stresses exceed the breaking point of the material itself.

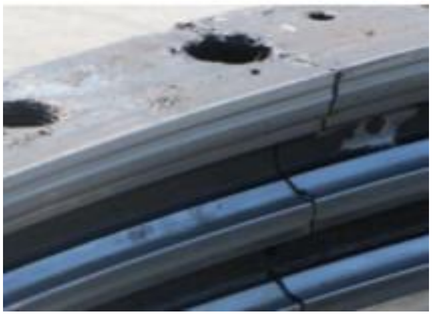


Figure 19. Overload fracture.

Fracture by fatigue: The fracture of a component by fatigue occurs when repeatedly exceeding the fatigue resistance of the material under stress, torsion or bending stresses.

2.4.3.3.2. Rolling Contact Fatigue

The mechanical fatigue of bearings is conditioned by the load conditions, dynamic and/or cyclic, to which the bearings are subjected to in their applications. This degradation mechanism mainly affects the raceways, due to the concentrations of stress generated by their contact with the rolling elements. Regarding the failure modes developed by the bearings under this type of stress, two types are distinguished: surface and sub-surface fatigue.

Surface fatigue: it is generated when the contact surface is subjected to cyclic tensions that exceed the fatigue resistance of the material.

Sub-surface fatigue: The contact between the raceway and the rolling element generates significant stresses not only of compression, but also of tension and shear, at a certain distance from the surface of the track. The cyclic tensions of traction and shear cause the appearance of micro-cracks around the inclusions of the bearing steel. Once created, the fatigue propagates these cracks towards the surface of the track producing flaking, pitting and the subsequent peeling of the surface.

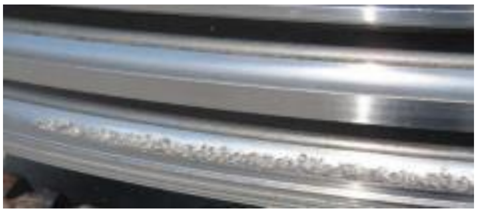


Figure 20. Fatigue fracture of raceways.

2.4.3.4. Inputs and outputs

The inputs required by the Diagnosis and Prognosis methods are:

- Numeric model of the bearing obtained from the FEM model;
- Time series from sensors in the blade bearing;
- Pitch angle;
- Data based on rolling tests and fatigue of the material.

The outputs that will be obtained are:

- Accumulated damage for the raceways zones of a given bearing;
- Historical evolution of the damage over time;

- Accumulated damage of the overall bearing corresponding to the most critical damage;
- Estimated useful life of the bearing.

2.5. Electrical Drive Train (Generator, Converter & Transformer) diagnosis / prognosis orientation (Task 2.5)

2.5.1. Introduction (Task 2.5)

EDF Group is especially knowledgeable in the behaviour of electrical equipment's, having notably in-depth knowledge of failure modes associated to conventional generation units. Within WP2 of ROMEO project, the aim of the EDF Group is to make use and develop further this knowledge, adapting it to offshore wind turbine generation units, taking into account their specificities. The development of specific diagnosis and prognosis algorithms will enable an improved Operation and Maintenance.

Quite often electrical failures seem to appear suddenly, this is either due to the very brevity of the physical mechanisms of the degradation pattern, and/or due to the lack of adequate observability. Most available operational data on conventional wind turbines correspond to 10-minute average. In this context, 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.

In WP2, to cope with the lack of adequate data characterizing the electrical failure modes, a mixed approach has been defined with simulation and the use of a small-scale test bench, adapted to generate failures. This approach having already been successfully led for conventional generation units. Different phases have been defined:

- A design phase:
  - for the diagnosis & prognosis algorithms for the following equipment: generator, transformer, DC bus of the converter;
  - for the adaptation of the small-scale electrical test bench (section 2.5.2) to fit the purpose of representing normal and abnormal operation with generated failures.
- An implementation phase: corresponding to the implementation of the adapted small-scale test bench itself, and to the implementation of the diagnosis & prognosis algorithms.
- A validation phase with upscaling:
  - Validation of the algorithms on small scale test benches;
  - Realisation of failure modes datasets in normal & abnormal operation;
  - Development of an upscaling methodology for application and validation on full scale configuration.
- A full-scale test bench phase: Siemens Gamesa will provide operational data associated to a full-scale generator. These data will be used for full scale application of the algorithms and for the validation of the upscaling methodology;
- A portability phase.

The electrical drive train configuration taken into account is based on the use of a permanent magnet synchronous generator, that is a common technical choice for new offshore wind turbines. The failure modes studied by EDF within WP2 are:

- Generator internal short-circuits: interturn short-circuits, phase to phase short-circuits, phase to neutral short-circuits;

- Generator loss of magnetization;
- Transformer interturn short-circuits;
- DC bus capacitor degradation;
- Converter/semiconductor failure diagnosis.

The following sections presents:

- General views on failure mode diagnosis & prognosis;
- Reduced scale test bench set up for ROMEO;
- Information associated to the various failure modes and algorithms associated.

2.5.2. Testing phase and data generation (Task 2.5)

The test bench is located in EDF R&D premises at Palaiseau, France, inside a laboratory dedicated to the study of electrical motors and generators. It was mainly specified in 2017, the equipment have been purchased in 2017 and 2018. The reception of the equipment has been made mainly in 2018, with last equipment received in first semester of 2019. Final implementation of these equipment with a fully operational test bench will be done mid-2019.

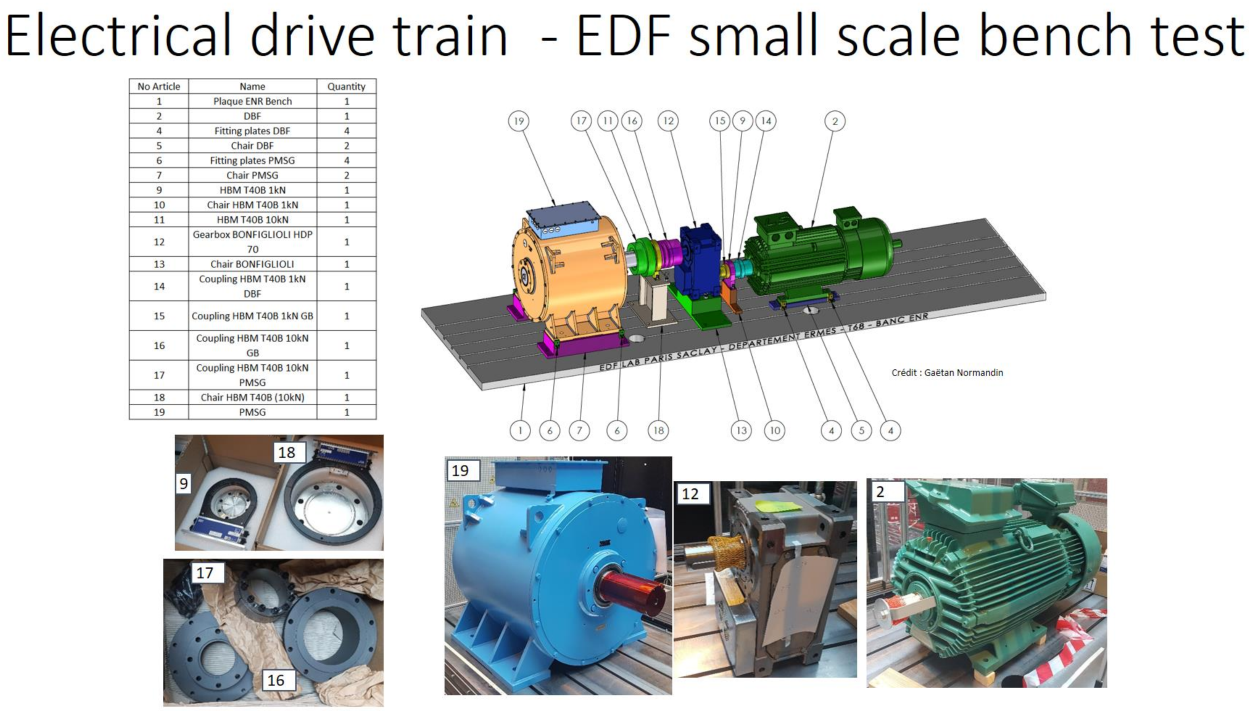
The machines studied on the test bench were chosen for their electrical and magnetic architecture, which are identical or similar to the generator of offshore wind turbines. For instance, the current configuration will have a permanent magnet synchronous machine (PMSM) and a doubly fed induction machine (DFIM).

The test bench has been designed to be reversible, both electrical machines can work in generator or motor mode at variable speed. The motor will reproduce the rotation of the wind turbine's rotor blades, via torque and speed control. The generator and power electronics will reproduce the wind turbine's generator, the converters, transformers and the connection to the network.
With this configuration, two different types of turbines can be studied without having to modify the test bench. However, it requires more development as the control system and the power electronics need to be able to switch between these modes.

The test bench is constituted of:

- A clamping plate for electrical machines, with housing;
- Two electrical machines: a motor and a generator; (red & brown)
- A gearbox;
- Mechanical and electrical sensors;
- Four cabinets of power electronics developed by EDF R&D;
- A control system developed by EDF R&D.

Figure 21 presents a scheme of the test bench with main equipment, excluding the transformers, the power cabinets housing the converters, the real time control system.



No Article	Name	Quantity
1	Plaque ENR Bench	1
2	DBF	1
4	Fitting plates DBF	4
5	Chair DBF	2
6	Fitting plates PMSG	4
7	Chair PMSG	2
9	HBM T40B 1kN	1
10	Chair HBM T40B 1kN	1
11	HBM T40B 10kN	1
12	Gearbox BONFIGLIOLI HDP 70	1
13	Chair BONFIGLIOLI	1
14	Coupling HBM T40B 1kN DBF	1
15	Coupling HBM T40B 1kN GB	1
16	Coupling HBM T40B 10kN GB	1
17	Coupling HBM T40B 10kN PMSG	1
18	Chair HBM T40B (10kN)	1
19	PMSG	1

Figure 21. Small scale electrical test bench scheme and main equipment.

With the test bench, the following tests are possible (without or with adaptations):

- Short-circuit on rotor and stator windings;
- Resistive imbalance between phases (slip ring faults);
- Eccentricity, bearing faults, gearbox faults;
- Power electronics faults;
- Simulated grid fault: lightning shock, rise or drop of frequency and voltage;
- Loss of communication with control system or monitoring system;
- Sensor breakdown;
- Reaction time of protection;
- Generator behaviour with grid interaction;
- Effect of reactive power regulation, ancillary services.

The sensors allow the monitoring of:

- Winding temperatures;
- Air gap flux;
- Voltage, Current;
- Torque, Rotation speed, Vibrations, angular position of the rotor.

The doubly fed induction machine is a 3 phase, 4 poles machine with a rated power of 55 kW, a rated stator voltage 400V, a rated rotor voltage 410 V, a rated speed 1468 rpm.

The permanent magnet synchronous machine is a 9-phase, 30 poles machine with a rated power of 55 kW, a rated stator voltage of 335V, a rated speed of 200 rpm.

The 4 power converters cabinets are each rated at 100 kW with a rated output voltage of 400 V. Three are used for the PMSM, one is used for the DFIM.

The 4 transformers are dry transformers rated at 100 kW.

The real time control system is based on an OPAL-RT system. The sampling rate for the observed electrical data is 20kHz.

For the generation of faults associated to:

- the PMSM: the PMSM stator windings have been specifically designed and adapted with appropriate connections so that various kind of short-circuit can be represented (inter-turn short-circuits, phase to phase short-circuits, phase to neutral short-circuits);
- The DC bus: no specific modification was required, accessibility to the DC bus enables to test various equipment;
- The converter: the control system is designed by EDF R&D, with a full control on the individual IGBT, enabling to represent the effect of internal failures;
- The transformer: no specific internal modification of the transformer has been done, nevertheless the fault can be represented with external impedances to represent the associated imbalance.

2.5.3. Generator short-circuits diagnosis / prognosis orientation

2.5.3.1. Aim

The aim of this module is to perform a diagnosis and a prognosis associated to the permanent magnet synchronous generator and failure modes associated to short-circuits (inter-turn short-circuits, phase to phase short-circuits, phase to neutral short-circuits). The goal is, based on the physical model, to provide an efficient diagnosis & prognosis enabling, either to prevent or to limit the effect of a failure thanks to an early detection, with possibly an anticipated and efficient maintenance action.

2.5.3.2. Failure description

Internal short-circuits of stator windings can be associated to:

- damages of the wire insulation due to vibrations of the stator windings, of the magnetic core, due to loss of insulation associated to overheating;
- damages in connections.

For interturn short-circuits several turns of a coil are short-circuited, resulting to an imbalanced state with corresponding harmonics in voltages and currents. The severity of the short-circuit depends on the number of turns short-circuited and the fault resistance. If this type of short-circuits can be of minor importance initially, with a generator still operating, it can then evolve in more important short-circuits.

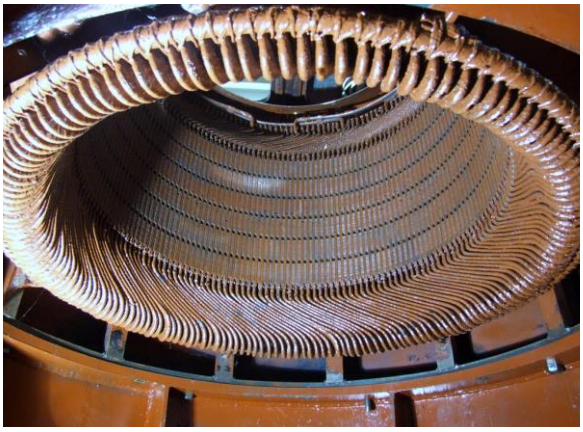


Figure 22. Stator of a pump motor.

Coil short-circuits, phase to phase short-circuits, phase to neutral short-circuits, have a higher impact on currents resulting generally to a fast action of the protection system.

2.5.3.3. System description

The generator that will allow diagnosis has a special configuration at EDF laboratory. The system is the stator of the synchronous permanent magnet generator. Multiple configurations are possible with variations associated to the number of phases, the number of poles, the spatial organisation of the stator windings, their repartition in the stator slots, the modularity of the design.

This variation of arrangements allows to monitor directly the variability of the configuration in the stator windings (measuring voltage and current) in order to develop a diagnosis and prognosis system.

2.5.3.4. Validation methodology

The small-scale test bench has been adapted so that to be able to generate faults on the stator windings. Notably few turns of a coil have been provided with appropriate connections so that to perform interturn short-circuits. The validation of the diagnosis & prognosis algorithms will be based both on the use of measurements of faulty operation with the small-scale test bench, and on simulations.

2.5.3.5. Inputs / Outputs

Inputs of the models are high frequency voltages and currents measurements. The outputs are:

- A physical indicator representative of the short-circuit severity;
- An indicator of the type of short-circuit;
- An estimated time to failure.

2.5.4. Generator loss of magnetisation diagnosis / prognosis orientation

2.5.4.1. Aim

The aim of this module is to perform a diagnosis and a prognosis associated to the permanent magnet synchronous generator and the loss of magnetization. The goal is, based on the physical model, to provide an efficient diagnosis & prognosis enabling, either to prevent or to limit the effect of a failure thanks to an early detection, with possibly an anticipated and efficient maintenance action.

2.5.4.2. System description

The system is a permanent magnet synchronous generator, that is the most common type of generator used in new offshore wind turbines. These generators are driven by full power converters that enable the large capabilities in speed variations. Depending on design choices, a low rotational speed (direct drive) or medium rotational speed (one stage gearbox) can be achieved by increasing the number of poles (and with it the size of the generator). Several variants of design are possible for these generators, notably with respect to the number of poles, the number of phases, the geometrical positioning of the rotor magnets, the organization of the stator windings, the architecture of the converter system driving them.

2.5.4.3. Failure description

The loss of magnetization of a permanent magnet can be due to overheating, high short-circuit currents, and depending on design choices of the control system to field weakening operations, to mechanical cracks within the magnets. It corresponds to a reduction of the induction of the considered permanent magnet, that contributes to create an imbalanced state. This state is associated to voltage, current and torque harmonics.

2.5.4.4. Validation methodology

The validation methodology is planned to be based partly on simulation works and partly on comparisons with small scale test benches results. Loss of magnetization will be characterized with simulation work, then to assess the selectivity, the evaluation of the algorithm will be both tested with simulated results test bench results associated to various type of faults.

2.5.4.5. Inputs / Outputs

Inputs of the models are high frequency voltages and currents measurements. The outputs are:

- A physical indicator representative of the magnetizing state;
- The phase associated to PF intervals for the failure mode;
- An estimated time to failure.

2.5.5. Transformer short circuit and structural integrity diagnosis / prognosis orientation

2.5.5.1. Aim

The aim of this module is to perform a diagnosis and a prognosis associated to the transformer and the interturn short circuit failure mode. The goal is, based on the physical model, to provide an efficient diagnosis & prognosis enabling, either to prevent or to limit the effect of a failure thanks to an early detection, with possibly an anticipated and efficient maintenance action.

2.5.5.2. Failure description

The failure mode described in this document is the inter-turns short-circuit of the transformer windings. This failure induces extra current in the short-circuited section, leading to over-heating in the zone and malfunctioning of the transformer, as it can be seen in Figure 23.
Inter-turns short-circuit in the transformer windings can be due to the loss of insulation proprieties of the windings or of the oil. The loss of winding's insulation proprieties is due to over-heating in the transformer or electrical faults such as phase short-circuit. The loss of oil's insulation proprieties is due to the environment and the over-heating in the transformer.

Figure 23. Transformer inter-turns short-circuit failure.

The possibility of modelling the transformer using the Arrhenius equation or the Wholer curve would serve to cover the structural integrity of the transformer core in the same chapter [30].

2.5.5.3. System description

The power transformer is a static component with two or more windings which, by electromagnetic induction, transforms a system of alternating voltage and current into another system of voltage and current usually of different values and at the same frequency for the purpose of transmitting electrical power.
In the test bench, the transformer is a dry 100kVA transformer with a primary and a secondary rated voltage of 400 V. In full scale offshore wind turbines, the rated apparent power is slightly higher than

the rated power of the generator. The rated voltage of the primary is, depending on the wind turbine, between 690 V and few kV. The rated voltage of the secondary is generally 33 kV or 66 kV.

2.5.5.4. Validation methodology

The validation methodology of the diagnosis & prognosis models is based on a combination of detailed simulations and test bench characterisation with simulated imbalances representative of inter-turn short circuits.

2.5.5.5. Inputs / Outputs

Inputs of the models are high frequency voltages and currents measurements. The outputs are:

- A physical indicator representative of the state of the transformer;
- The phase associated to PF intervals for the failure mode;
- An estimated time to failure.

2.5.6. DC bus capacitor degradation diagnosis / prognosis orientation

2.5.6.1. Aim

The aim of this module is to perform a diagnosis and a prognosis associated to the degradation of the capacitor of the DC bus of the converter system. The goal is, based on the physical model, to provide an efficient diagnosis & prognosis enabling, either to prevent or to limit the effect of a failure thanks to an early detection, with possibly an anticipated and efficient maintenance action.

2.5.6.2. Failure description

A progressive decrease of the capacitance is observed with an increase of the equivalent series resistance.

2.5.6.3. System description

The system considered is the capacitor of the DC bus of the converter system.

2.5.6.4. Validation methodology

Using the small-scale test bench, different modifications on the DC bus will be possible enabling the measurements of a simulated degraded state. This will be used for the validation of the diagnosis & prognosis algorithm.

2.5.6.5. Inputs / Outputs

Inputs of the models are high frequency DC voltage and current measurements. The outputs are:

- A physical indicator representative of the state of the capacitor;
- The phase associated to PF intervals for the failure mode;
- An estimated time to failure.

2.5.7. Converter semiconductor failure diagnosis / prognosis orientation

2.5.7.1. Aim

The aim of this orientation is to perform a diagnosis and a prognosis associated to the degradation of the semiconductor elements in the converter system. The goal is, based on the physical model, to provide an efficient diagnosis & prognosis enabling, either to prevent or to limit the effect of a failure thanks to an early detection, with possibly an anticipated and efficient maintenance action.

2.5.7.2. Failure description

A malfunction would be observed close to the failure. This may be observed by the different outcomes on the voltage phases on the converter, as well as in the temperature trends. By using the test bench in high sampling frequencies, a subset of methods detecting outliars is extrapolated.

2.5.7.3. System description

The system considered are all the semiconductor elements in the converter system.

2.5.7.4. Inputs / Outputs

Inputs of the models are high frequency voltages in the converter and the temperature profile of each of the elements. The outputs are:

- A physical indicator representative of the state of the semiconductors in the converter;
- The phase associated to PF intervals for the failure mode;
- An estimated time to failure.

3. Conclusions

This document covered the orientations for the development of new diagnosis and prognosis solutions within WP2 of ROMEO project. Each orientation presented the possibility to exploit a separate technology that allows the ROMEO partners to further port these technologies to the field or to sell licenses for them.

Section 2.3 covers the task related to the diagnosis and prognosis solution for the drive train (mainly gearbox and main bearing). A part of this task, a subset of new designs has been developed and are available with the most updated hardware to be deployed in offshore wind turbines, giving provisions for earlier detection and better prognosis of future failures affecting not only the drive train but also the rotor blades. The extended coverage of further failure modes and the development of prognosis solutions will imply a significant improvement of the State-of-the-Art solutions.

Orientations for diagnosis and prognosis solutions for the Blade Bearing are presented in section 2.4. A brand-new blade bearing CMS has been developed and will be suitably installed in new turbines. A retrofit or a new installation will be particularly suitable for large diameter offshore wind turbines. This is an extremely important advance of the State-of-the-Art as no solutions are currently available for monitoring the condition of wind turbine blade bearings.

Finally in section 2.5, Electrical Drive Train diagnosis and prognosis techniques have been defined in order to boost the electrical capabilities for detection and prognosis of both Siemens Gamesa and EDF, working on a collaborative effort. Given that a proper sensor and frequency configuration from EDF Small Test bench will effectively detect Electrical Drive Train predefined failures, the design may be exported and built in in the newest offshore wind turbines.

As it has been mentioned in section 1.1 the FMECA sessions in WP1, together with the feasibility to perform diagnosis and prognosis was a determinant factor to proceed with the orientations presented in this document. However, as the orientations have been built and the state of the art is advancing, it may be possible that in the future, the same failure modes are become relevant for further investigation.

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