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Digital Models for Floating Offshore Wind

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1 Nomenclature

Abbreviation	Description
API	Application Programming Interface
AR	Augmented Reality
BFOWF	Bottom-fixed offshore wind farm
BIM	Building Information Modelling
BSI	British Standards Institution
CAD	Computer-Aided Design
CAPEX	Capital Expenditure
CBM	Condition Based Maintenance
CM	Condition Monitoring
DT	Digital Twin
FOWF	Floating Offshore Wind Farm
FOWT	Floating Offshore Wind Turbine
GIS	Geographic Information System
GNSS	Global Navigation Satellite Systems
HSE	Health, Safety and Environment
IMUs	Inertial Measurement Units
ISPs	Individual Service Providers
KPIs	Key Performance Indicators
LCOE	Levelised Cost of Energy
LiDAR	Light Detection and Ranging
LoD	Level of Detail
MDT	Mean Down Time
MTBF	Mean Time Between Failure
MTTF	Mean Time To Failure
MTTR	Mean Time To Repair
O&M	Operations and Maintenance
OPEX	Operational Expenditures
OSS	Offshore Substation
RDS-PP	Reference Designation System for Power Plants
SCADA	Supervisory Control and Data Acquisition
SHM	Structural Health Monitoring
TDT	True Digital Twin
TSOs	Transmission System Operators
UNIDO	United Nations Industrial Development Organisation
VR	Virtual Reality
VSL	(Ramboll’s) Virtual Solutions Lab
WF	Wind Farm
WTG	Wind Turbine Generator

2 Executive Summary

Despite having a great potential, the current costs of floating offshore wind prevent it from being deployed massively at a global scale. This situation is driving many research works to improve the floating wind feasibility and speed up its implantation. One of the newest fields of innovation is the digitalisation of assets, which applied to the floating wind farms can lead to a reduction of their LCOE. The reasons include the complexity of the floating wind projects, the large investments required, the size of the components, the environments where the farms are installed and the inherent accessibility and workability issues.

Other technologies have been digitalised before the floating wind industry, therefore there is already experience in the industry and general guidelines can be extracted. A key stage where the digitalisation can lead to an LCOE reduction is the maintenance, and the first step is determining the typical failures that occur in a floating wind farm. As the floating wind technology is still advancing on its first steps, there is a noticeable lack of failure rates of floating wind components and some of them have been extracted from the bottom-fixed technology or the oil and gas platforms. An inverse relationship between failure rates and repair times is observed and fatigue and corrosion are identified two critical failure causes.

Digital twins are digital models that behave like the real asset and their development is particularly relevant for the floating offshore wind farms. Their usage can lead to early failure detection, reduced repair times and increased availability of the wind farms. A digital twin of a complete generation unit (from the rotor to the anchors) has been developed in the context of the COREWIND project, in which a number of inputs are entered into a machine learning model that provides multiple outputs. As an example of the applicability of the digital twin, a mismatch between the model outputs and the real measurements onsite may indicate a failure of a wind turbine component. The measurements required by the digital twin are key and must be accurate. There are a number of sensors to measure different types of data according to the typical failures, including 3D positions, vibrations, strain, temperatures and acoustic analysers.

A different type of digital models are the control models working on a wind farm level. These models allow improved functionalities compared to independent turbine controllers. A wind farm control model has been developed to extend the lifetime of the wind turbines, working to equalise the fatigue over them. This is related to the wake effects and the fact that the turbines in the perimeter of the site experience greater fatigue with the standard controls. With the control developed model, a uniform fatigue damage is achieved for all the turbines, allowing a life extension from 25 to 30 years, leading to a reduction of a 4% of the LCOE.

Applying the innovations of the building industry in terms of data unification and visualisation, the Morro Bay floating wind turbine no. 11 (WTG-11) is used as a reference WTG, and an exemplary BIM (Building Information Modelling) 3D model of the WTG is created. The semi-submersible foundation CAD model was converted into a 3D model using the virtual reality software Unity [1], and 360° images were extracted as input for RamView360 to create the BIM model. Following the creation of the BIM Model in RamView360, annotation points are mapped in the 3D environment to display asset information, O&M tasks, documents, and so on. Six annotation points are created in the COREWIND exemplary model to demonstrate six different RamView360 use-cases. This finalised BIM model will be included as a key deliverable in the RamView360 tool. The RamView360 tool can then be linked using shared URLs or QR code function in the tool. This BIM demonstrates effective use of 3D BIM visualisation tool to utilize for different use-cases during whole life cycle of the wind farm. The COREWIND demo can be accessed through following weblink and credentials. In chapter 7.3 the detail overview of the demo model is described.

Demo web-link:	https://ramview360.xyz/Corewind/	
Login Credentials:	Username:	Corewind_RamView360
	Password:	Corewind_2020%RAM$

All the presented innovations developed in the context of the COREWIND project improve the understanding, monitoring and control of the wind farm assets from different perspectives as well as the collaboration between multidisciplinary teams, leading to an LCOE reduction of the floating wind technology and boosting its early global deployment.

3 Introduction

The COREWIND project investigates the influence of different design, manufacturing, installation, maintenance and decommissioning strategies as well as new requirements during its lifecycle in the prospect of future floating offshore wind farms. The installation and maintenance of floating wind farms are major cost drivers that motivate the assessment of new strategic opportunities and developments to reduce the wind farm costs.

A key opportunity to further improve floating wind is its digitalisation, as the technology is relatively mature and can lead to significant cost reductions. These savings are achieved by using digital models to have a better understanding of the wind farm components and their real-time state, as well as to increase the wind farm controllability.

This study begins with a deep revision of the state of the art of the available digital tools. As the maintenance is a key area where several improvements and cost reductions are expected, special focus is given to the failures of the offshore wind farms, as their knowledge is crucial to reduce their impact and improve their detection. The available sensors for wind farm monitoring are also reviewed because they are used to feed the digital models, therefore their details and applicability must be known. The state of the art of the digital twins and BIM-based toolboxes are also presented, as new models have been developed in the context of the COREWIND project.

Chapter 5 presents the digital twin model developed as part of the COREWIND project. The aim of the digital twin is replicating the behaviour of the wind farm during its operation to remotely identify but also foresee failures having as inputs the information provided by onsite sensors. To that purpose, a machine learning algorithm is developed and validated, and a graphical interface is created to interactively access the model outputs in real time.

Chapter 6 includes a model to control the wind farm with the aim of reducing the fatigue on its components. This reduction can lead to increased wind farm lifetimes. The challenges to be faced with are described, followed by the developed model and the obtained results after its application in a simulated case.

This study concludes in chapter 7 with the BIM model of a wind turbine that eases the understanding of the wind farm components in a graphical environment. The developed model can be accessed online and the accessing details are also provided. The use cases of the model are described in the chapter, including a detailed explanation of two of them.

In all, this document provides a complete analysis of the digital tools available in the market, the required knowledge and hardware, different models developed specifically for the floating wind industry and the challenges and next steps to carry out to further improve the technology with the final goal of reducing its LCOE.

4 State of the Art on Digital Models

Currently, there are only three floating wind farms in operation: Hywind Scotland (30 MW, commissioned in 2017), WindFloat Atlantic (25 MW, commissioned in 2020) and Kincardine (50 MW, commissioned in 2021). The LCOE of the former 2 is around 200 €/MWh [2] [3], while current studies reflect a substantial reduction to 95 - 160 €/MWh depending on the site [4] [5] [6]. Even if the lowest values are deemed realistic, the technology is not competitive yet, therefore further cost reductions must be carried out to achieve a global deployment.

Compared to onshore and BFOWFs (Bottom-Fixed Offshore Wind Farms), one of the factors that increase the LCOE of FOWFs is the difficulty to perform on-site operations: installation, maintenance and decommissioning. The available weather windows to perform such operations are reduced because the wind farms are typically located in sites with strong winds, related to extreme sea conditions. Furthermore, the weather limits are more restrictive because both the vessels and the substructures are floating, which increases the relative motions between them and complicates the access to the floaters as well as the use of cranes from the vessels. These factors multiply the costs of a technology that has a high baseline because the large components transportation requires towing or big cranes, compared to jack-up vessels for FBOWFs or truck for onshore farms.

More specifically, the reduced time windows to perform offshore operations are particularly critical to conduct the maintenance activities. In the case of preventive (scheduled) tasks, it leads to seasonal campaigns (summer in Europe), concentrating the activities which increases the costs. On the other hand, the corrective (unscheduled) maintenance activities derived from failures can have a significant impact on the energy production due to downtime, as the full farm or part of it may be stopped for a long period if a suitable weather window is not foreseen when needed.

Having a deep knowledge of the state of health of the wind farm components is crucial to make the correct decisions related to the maintenance, converting corrective activities to preventive activities. Additionally, early detection of failures can lead to smaller impacts on the energy produced and lower the repair costs, as they can be addressed sooner when their consequences are less relevant. Both tasks can be achieved by means of accurate digital models that provide relevant information and online continuous monitoring systems whose measurements are the model inputs.

Two of the main digital models are the Digital Twins, described in section 4.3, and the BIM models, whose details can be found in section 4.4. In order to define the relevant outputs of the models, first the failures must be assessed (section 4.1), as the target is their identification. An analysis of the available monitoring sensors is contained in section 4.2. Finally, the outcomes are presented in section 4.5.

4.1 Failures in offshore wind farms

The failures characterisation is important due to their significant impact on the LCOE. Figure 4-1 shows the annual failure rates and corresponding downtimes for offshore wind turbines. It can be observed an inverse relationship between the failure frequencies and the repair times. While the generator is typically repaired in a week, it has one of the lowest failure rates; on the other hand, the electrical system has the highest failure rate, but it has one of the lowest repair times. Figure 4-2 provides a list of wind farm components sorted by criticality, being the power converter the most critical element, followed by the pitch system and the yaw system. The hydraulic system was also identified as a critical component, making up a 13% of the overall failures together with the pitch system [7]. The same study determined an average failure rate in offshore wind farms of 8.3 failures per turbine per year. The main causes of failure of different systems are listed next.

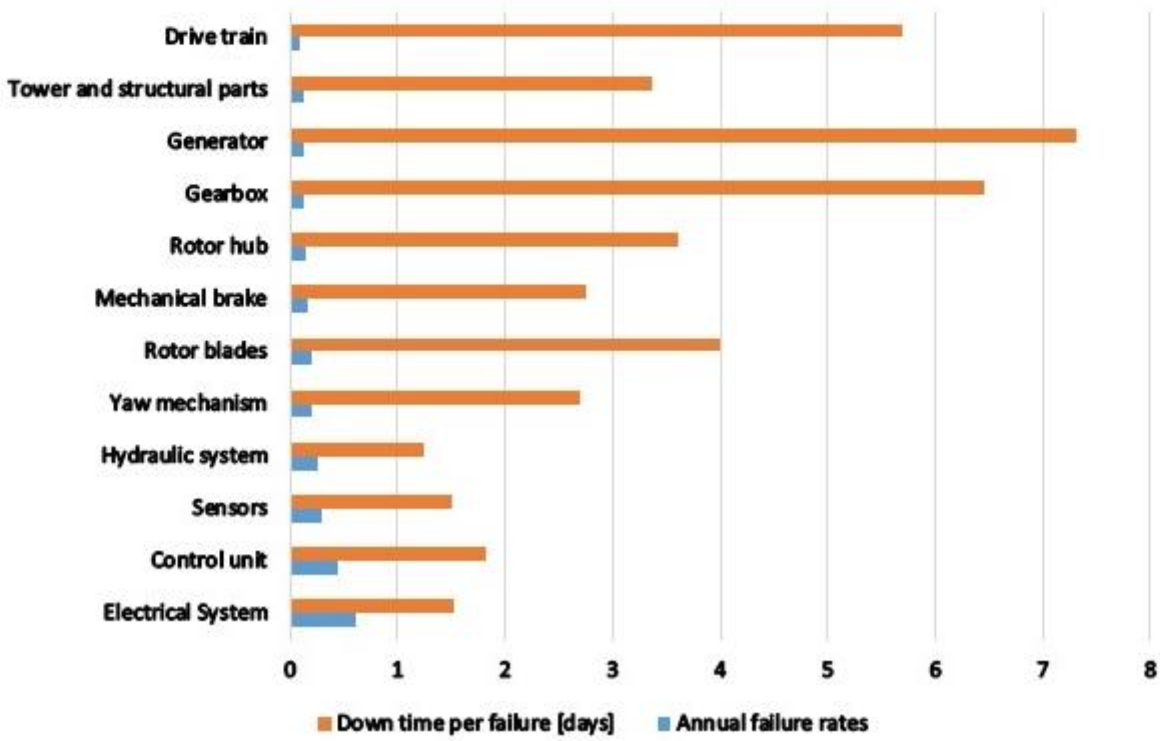

Figure 4-1. Annual failure rates of offshore wind turbines parts and corresponding downtime based on [8].

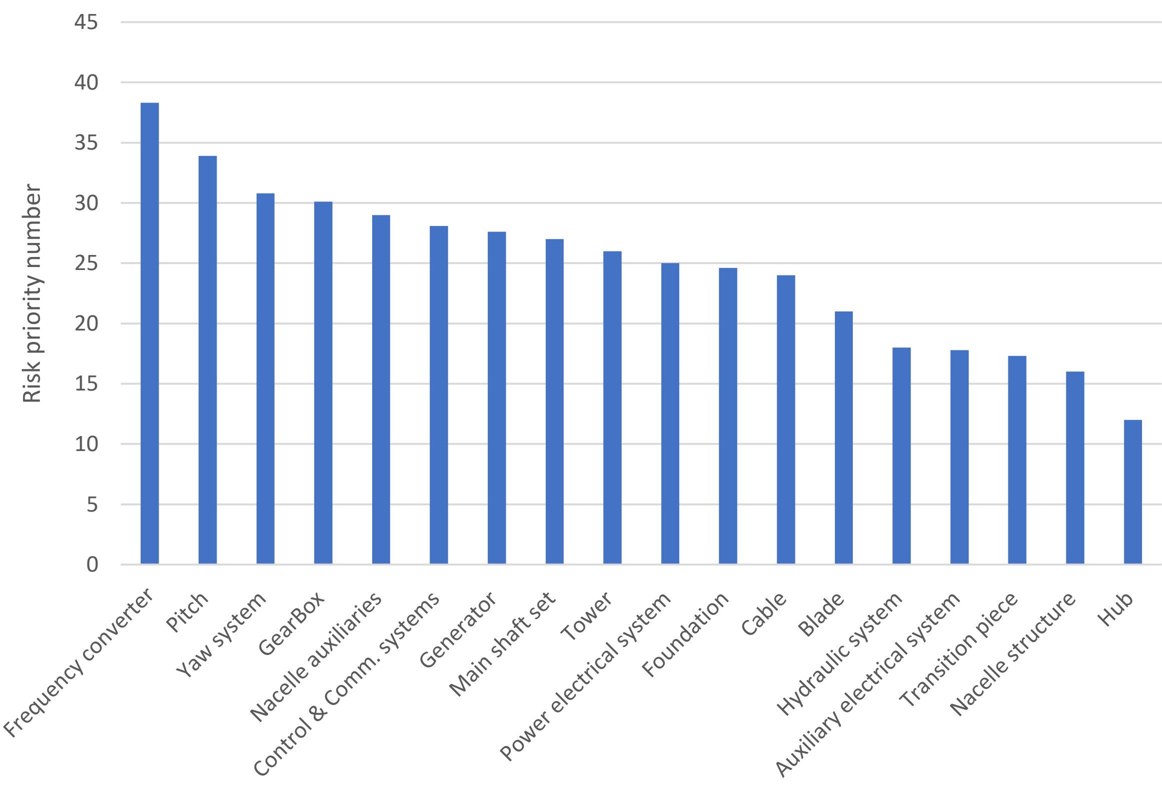

Figure 4-2. Wind farm components sorted by criticality according to [9].

4.1.1 Tower and substructure

Due to the vibrations derived from the extreme sea conditions, the tower can be fractured [10] [11]. On the other hand, the main causes of failure of the floater are:

- Fatigue.
- Corrosion.
- Welding cracking.
- Hull collision.

4.1.2 Mooring system

The information related to mooring system failures is retrieved from the oil and gas sector due to lack of data, where 0.03 failures per year were identified [12]. Other studies conclude 0.2 fails per platform can be expected in the whole lifespan [13].

Figure 4-3 shows the prevalent failure modes of mooring systems, where it can be observed that the fatigue and the corrosion are the causes of half of the failures. Corrosion is particularly relevant for mooring line chains because it steadily reduces the chain diameter, modifying the mooring system response. Mechanical damage can be caused during installation or inspection activities and the overload corresponds to excessive tension during storms and hurricanes.

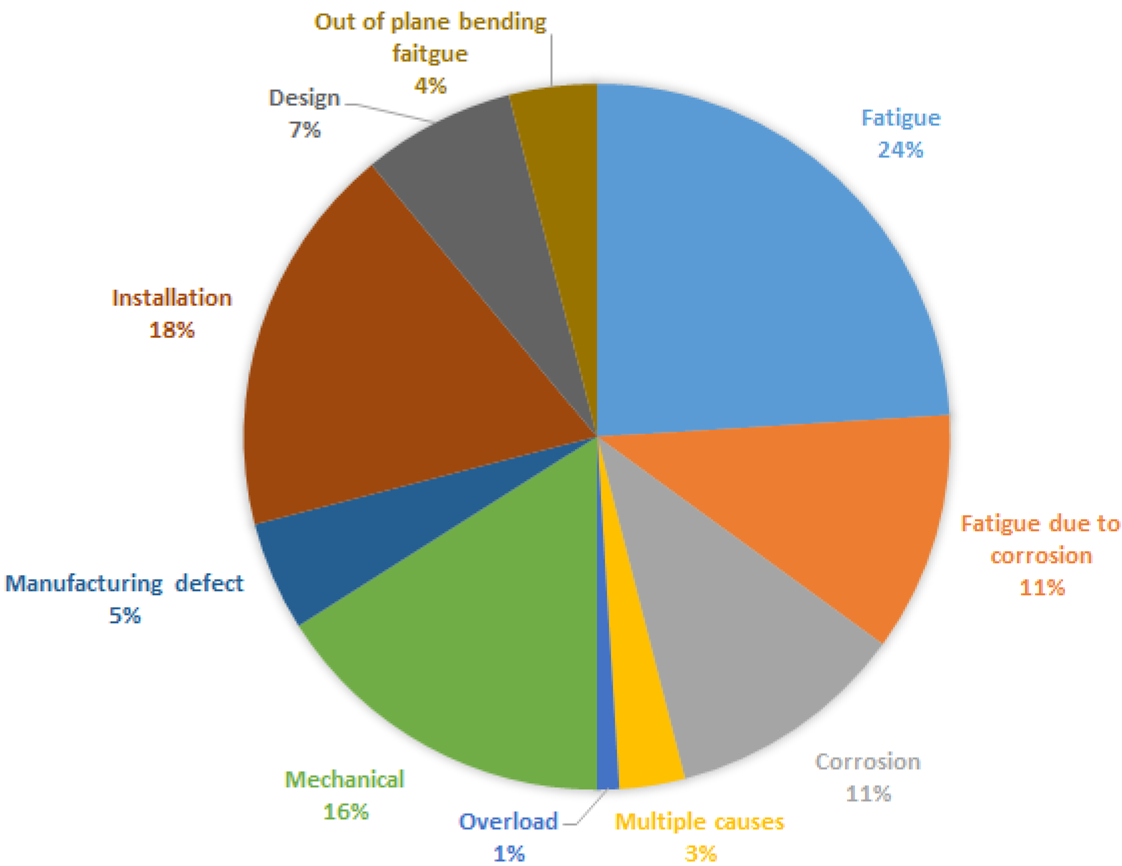

Figure 4-3. Prevalent failure modes in mooring systems based on [14].

4.1.3 Wind turbine

The wind turbines include a number of systems prone to fail and described below:

- Pitch and yaw systems. The main failures are related to the hydraulic system, the lightning protection and the limit switch [10] [11].
- Auxiliary system. A 61% of the auxiliary system failures are related to the electronic components [10] [11].
- Power converter. The most common failure occurs on the active switching component such as IGBTs and may be caused by overheating. The impact of the failure of the converter varies depending on the wind turbine technology; in offshore wind farms, where permanent magnet synchronous generation is typically used, all generation is lost in case of a converter failure.
- Generator. The origin of generator faults can be electrical, such as short-circuits, or mechanical, such as corrosion or dirt [10] [11].
- Gearbox. When present, the gearbox failures are related to the bearings corrosion, lubrication problems and vibrations [11] [15].

4.2 Sensors for Monitoring

There are a number of monitoring techniques, each used for a different component:

- Condition monitoring (CM) is conducted on rotating machinery and electrical components with high frequencies.
- Structural health monitoring (SHM) is performed on the substructure and the blades (medium frequencies) and can be divided into global or vibration-based monitoring and local monitoring.
- Supervisory control and data acquisition (SCADA) is used to monitor environmental and operational conditions (low frequencies).

A wide selection of monitoring techniques is described next.

4.2.1 Vibration-based damage detection

The vibration analysis is used to early detect failures in mechanical components because changes in the natural frequency of a structure may be caused by changes of its characteristics or geometry. It is applied to shafts, bearings and blades, among others. The sensors required are accelerometers, piezoelectric sensor and microelectromechanical systems (MEMS). Figure 4-4 shows the measurement setup of a bearing in a wind turbine gearbox.

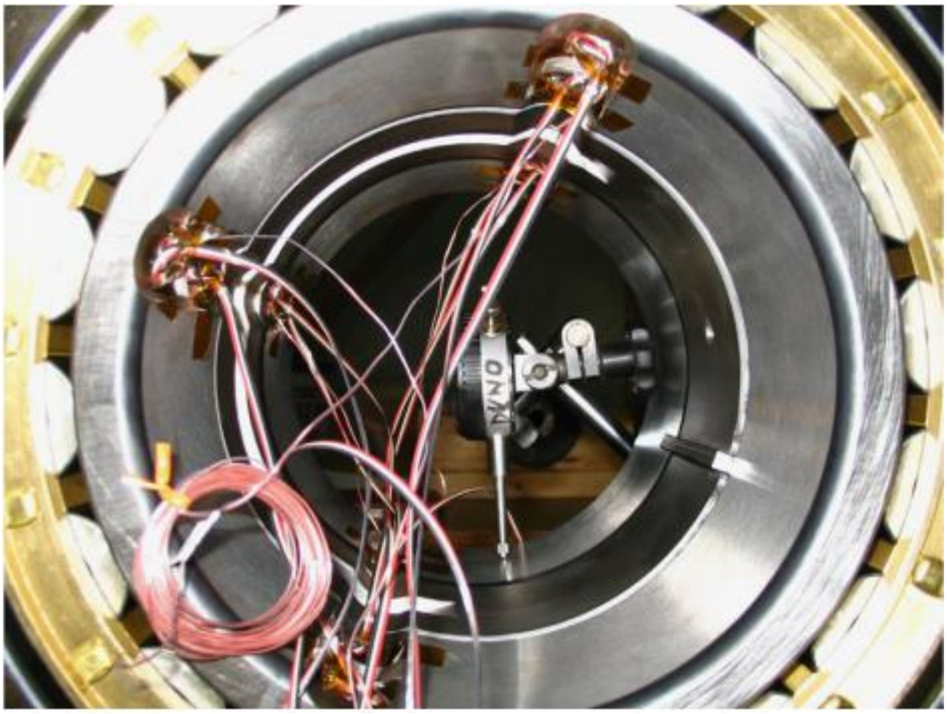

Figure 4-4. Instrumentation of a gearbox bearing [16].

4.2.2 Acoustic emission

The acoustic emission technique is usually applied to detect faults in gearboxes, bearings, shafts and blades. The damages detected include cracking, excessive deformation, debonding and delamination. This technique requires piezoelectric sensors with high sensitivity to capture the acoustic emissions. Figure 4-5 illustrates a blade with sensors to detect and locate cracks on its surface.

Figure 4-5. Blade section with acoustic emission sensors [17].

4.2.3 Oil analysis

Oil and valve issues represent about a 30% of the overall pitch/hydraulic failures: leaks and unscheduled oil changes and top ups [18]. To identify them, a number of tests are performed: viscosity analysis, oxidation analysis, water/acid content analysis, particle count, machine wear and temperature monitoring.

4.2.4 Temperature measurement

The temperature is monitored because changes in the temperature of components like bearings or generator windings may indicate a failure. This technique is typically combined with other methods [19]. To detect anomalies in the material beneath the surface, the thermal imaging method is used, which is based on the subsurface temperature gradients.

4.2.5 Strain measurement

Strain measurements are conducted as part of the SHM of blades and towers. The sensors used are typically foil strain gauges, fibre optical strain (FOS) gauges and linear variable differential transducers (LVDTs). FOS gauges are insensitive to lightning, which has led to an increase in their use [8] [19]. On the other hand, LVDTs are immune to the magnetic fields generated by high voltage cables, but they are more expensive [20]. Strain gauges are also used for direct measurements of mooring loads in load cells and load shackles. Figure 4-6 illustrates a load shackle used in the DOVICAIM project [21].

Figure 4-6. 75 ton load shackle [21].

4.2.6 Optical fibre monitoring

This technique is used for the SHM of the wind turbines, placing optical fibres on the surface or embedded in the components. However, it is more expensive than other methods [19].

4.2.7 Ultrasonic testing

This technique is used for structural assessment of towers and blades. The basic principle is that ultrasonic waves are emitted by a transmitter and pass through the tested material, being picked up by a receiver unless reflected by flaws. This method can detect cracks of few millimetres [19]. The test can be performed as pulse-echo, through transmission and pitch-cath.

4.2.8 Photogrammetry

This technique is used to determine the 3D coordinates of an object by combining 2D images taken from different locations thanks to diagnostic software available in the market for online monitoring. Figure 4-7 shows the basic principle: a set of markers are placed on the object to measure and a number of cameras simultaneously register images. This technique can be used to carry out a dynamic analysis of the objects.

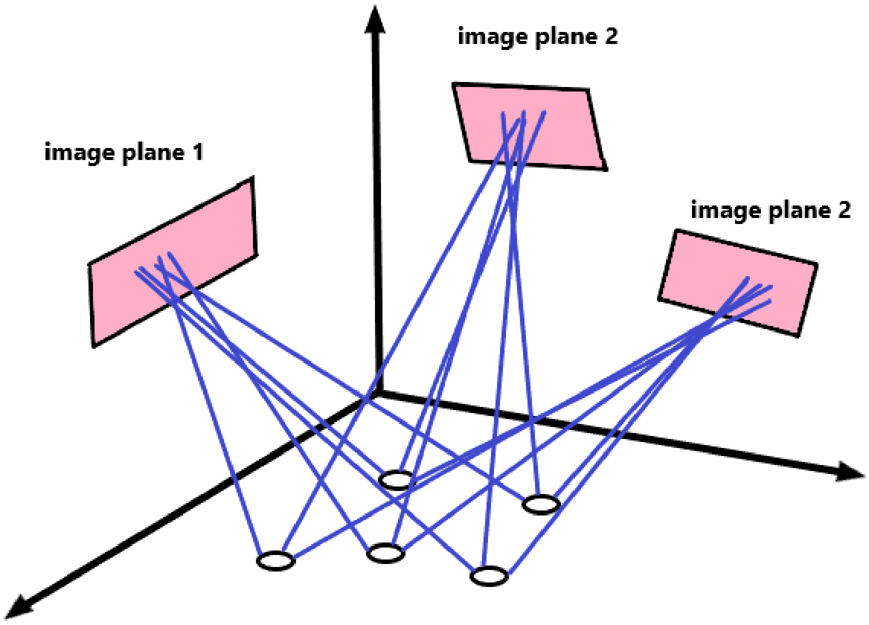

Figure 4-7. Simultaneous process of 2D images taken from different locations [22].

4.2.9 Inclination sensors and sonar

The inclination sensors are located along the mooring lines to determine their shape [23]. On the other hand, sonar techniques can also be used with the same purpose [24]. Both techniques are indirect measurements applicable to catenary mooring lines and useful for mooring line integrity studies.

4.2.10 GNSS

Current Global Navigation Satellite systems (GNSS) are geolocation systems allow accurate monitoring of motions and are generally applied to the platforms. The current technologies available are: GPS (USA), GLONASS (RF), BeiDou (PRC) and Galileo (EU). This technology is used to identify mooring line failures due to abnormal offsets of the platform given the environmental loads. Due to the output rates, GNSS can also be used to obtain velocities and accelerations of slow dynamic systems.

4.2.11 Inertial Measurement Units

Inertial Measurement Units (IMUs) consist of accelerometers and gyroscopes that estimate the acceleration and tilt of devices [25]. These devices are often a combined with GNSS for improved performance and increased output rate. Figure 4-8 shows a met mast that incorporates GNSS+IMU sensors to accurately determine the individual velocities of a number of anemometers.

Figure 4-8. Idermar met mast [26].

4.2.12 Summary

Table 4-1 summarises the most common monitoring methods for wind turbines and the sensors used.

Table 4-1. Monitoring methods and sensors [8] [27].

Method	Sensors	Components	Advantages	Disadvantages
Vibration analysis	Accelerometers, piezoelectric sensors, microelectromechanical systems (MEMS - more expensive)	Main shaft, main bearing, gearbox, nacelle, tower, foundation	Indicates both small and large damages, the sensors can be very cheap with high sensitivity	Often this method has to be supplemented by Finite Element method
Acoustic emissions	Piezoelectric sensors	Blades, main bearing, gearbox, generator, tower	Damage can be detected and located before it becomes visible, fatigue tests can be performed with this technique	Large number of sensors required, big number of outputs and cabling, the cost is high, appropriate for smaller structures
Ultrasonic testing technique	Piezoelectric wafer, actuators/transmitters and receivers (cheap, accurate and sensitive)	Tower, blades	Can be used for SHM, as well as for detecting surface defects, detects cracks of just a few millimetres from long distance, the cost is low to medium	Damage localisation is difficult
Strain measurement	Typical foil strain gauges, FOS (insensitive to lightning), LVDTs (expensive and accurate)	Blades	The sensors are reliable and accurate, can be also used for mooring system monitoring	Detection of small damages is difficult, the cost is very high, requires a large number of sensors
GNSS	GNSS receivers	Foundation	It is a useful method for monitoring platform movements	May require IMUs to be accurate

4.3 Digital Twins

A Digital Twin can be understood as a model-based representation of a real asset trained or developed using real data. A Digital Twin is made of three main parts: the real system, the virtual system and the information shared among the previous [28].

4.3.1 Digital Twin concept

Dr. Michael Grieves was the first to present the concept of a Digital Twin in 2002. He explains that the Digital Twin is more beneficial than a 3D model since it provides valuable information about the physical system such as functionality, behaviour under various settings, technical specifications, and so on. In his work [29], he characterised the Digital Twin notion as follows:

> *"Digital Twin (DT) – the Digital Twin is a set of virtual information constructs that fully describes a potential or actual physical manufactured product from the micro atomic level to the macro geometrical level. At its optimum, any information that could be obtained from inspecting a physical manufactured product can be obtained from its Digital Twin."*

Digital Twin technology is a novel approach to creating a digital copy of real assets that can be used to update the numerical mode, visualize and monitor asset condition, and maintain it over an entire lifecycle by simulating in near real-time using monitoring data. Digital Twins can be useful in many areas of the wind industry, including asset information systems, O&M optimisation, structure health monitoring, risk assessment, maintenance planning, and so on.

According to Balakrishnan, S.; et al. [30], the Digital Twin is the cutting-edge technology of the new 4th industrial revolution era. The concept of a Digital Twin is to create a detailed digital representation of the system in order to optimize the behaviour of the system/assets by using real-time environment scenarios via sensors. The Digital Twin concept is a synthesis of various DT enablement technologies such as the Internet of Things (IoT), cloud computing, data analytics, artificial intelligence, simulation modelling, 3D visualisation, and so on. These technologies aid in the creation of a strong Digital Twin concept based on the user's specifications. As the cost of sensors and computing hardware continues to fall, so have the total costs for DTs in recent years.

The DT concept may vary depending on the use case and user requirements. A simplification of the topic is used to aid comprehension. Figure 4-9 depicts an illustration of the DT idea. The digital world is a virtual representation of the real world. As input data, the digital world can be utilised as a reference model to simulate various scenarios or problems in the physical world. The iterative learning process aids in the implementation of many situations in the digital world and the identification of the most appropriate result. The simulation's results provide us with information on recommendations or actions that can be taken to better the physical world. For example, if we want to predict the effect of climate change on temperature, we must use real-world scenarios on the digital world model. Through an iterative learning loop, this digital world model simulates various scenarios and predicts the most suitable scenario as an output. As an example, we receive recommendations on how much CO_2 emissions we should reduce. Those recommendations can then be put into action in the real world to help mitigate future temperature rises.

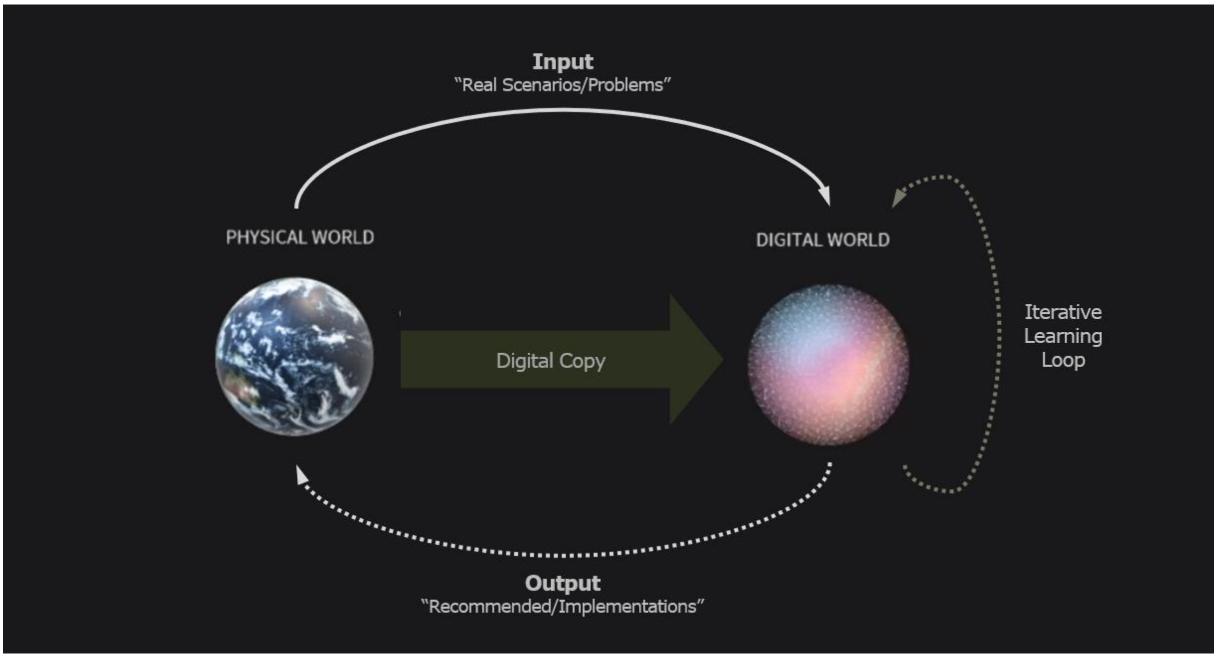

Figure 4-9 Digital Twin concept example.

Wang, Z. [31] provides a similar example, stating that data as input and information as output can be shared between real and virtual models. The feedback loop aids in the continuous improvement of the digital model. The level of detail of the DT model must be defined in accordance with user requirements. A corresponding virtual model can set up a DT model for specific industrial use-cases such as in a production facility, workshop application, factory lines, manufacturing resources, complex equipment monitoring such as jet engines, wind turbine structures, bridges, buildings, and so on [32].

The research paper by Haag, A. [33] demonstrates that the Digital Twin concept can be applied to any system in the world, from simple to complex. He mentions that a communication channel, such as web-based interactive software, can be useful in effectively monitoring the Digital Twin system. This communication channel provides useful information to the user by displaying 3D models with integrated asset data. This advanced technology is already being used in the next industrial revolution, known as Industry 4.0. According to Akulenko, E.; et al. [34], the DT concept has gained traction in the industry over the last decade. As a result, the DT concept is being used more frequently in emerging industries such as wind energy. Ramboll is also making a name for itself as a key developer of Digital Twin solutions for partners in the offshore wind energy industry [35].

The following steps are needed to develop a Digital Twin [36]:

- Data acquisition
- Model creation, update and validation
- Asset and model integration

There is an increasing interest in the Digital Twin development by using artificial intelligence (AI) techniques such as machine learning and deep learning. While researchers focus on fault detection, operation, maintenance and condition monitoring, the industry focuses on wind farm operation, wind turbine performance, state of health estimation and grid reliability. However, the field of Digital Twins applied to FOWTs is yet to be developed.

4.3.2 Visualisation of Digital Twin models

According to Revathi, A.R. et al. [37], visualisation is a graphical approach to representing a digital copy of a physical asset or system. The visualisation of the 3D model is the first step toward the establishment of a Digital Twin model. Visualisation is central to the DT concept because it presents useful information to the user while interacting with other DT enabling technologies. The level of detail of information/data can be used to classify DT models. According to Umamaheswari, R.; et al. [38], DTs can be defined from the highest to the lowest hierarchy, i.e. from the system level to the component level. He also provides an overview of how DT enabling technologies such as IoT, simulation, and so on play a key role in making the DT model more robust and realistic.

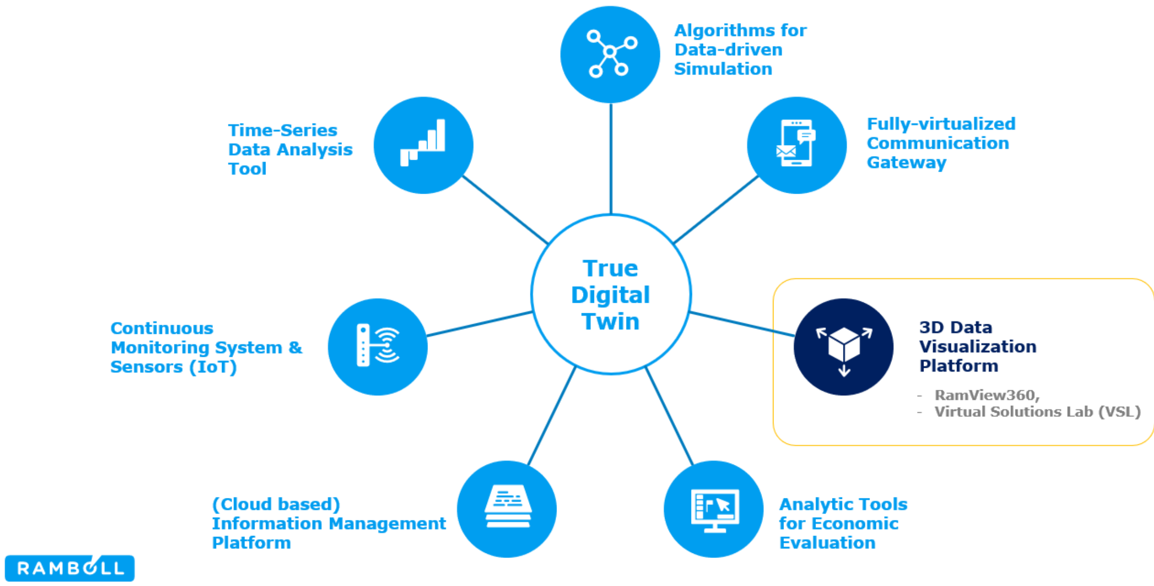

Figure 4-10 True Digital Twin Enabling Technologies (Industry 4.0)

Figure 4-10 depicts a list of key Digital Twin enabling technologies. These technologies contribute to the development of a Digital Twin environment to support activities in the wind energy industry. Each technology can be derived based on the use-case and level of integration with the DT environment required. True Digital Twin technologies rely heavily on 3D data visualisation. This is an example of how a user can easily interact with the tool to find specific information. The main challenge for visualisation tools is determining the optimal scope for specific applications throughout the wind farm's life cycle. The use of visualisation tools can vary depending on the needs of the user. As a result, it is necessary to identify the best ideas/concepts for the wind energy sector in order to effectively implement them. This study provided an overview of RamView360 visualisation tool use cases in the offshore wind industry as reported by various WF stakeholders.

Ramboll has created "RamView360," a web-based DT visualisation tool. The Ramview360 tool can display all types of Digital Twin models. This tool is compatible with any VR or VSL device. In RamView360, an exemplary Digital Twin model of the Morro Bay floating wind farm has been created to serve as a proof of concept model. This tool is used to visualize the Digital Twin model in 3D with overlaid information such as numerical values, KPIs, graphs, tables, etc.

4.3.2.1 What is Virtual Reality (VR)?

Virtual Reality (VR) is a technology that allows you to visualize a 3D/CAD model in a simulated environment with interactive user functionality. In contrast to the traditional 3D visualisation on screens in front of the user, VR Solution immerses the user in an interactive virtual environment that includes a digital blueprint of the actual wind turbine and wind farm. Refer to Figure 4-11 to see how the RamView360 tool works with VR glasses.

Offshore environmental conditions can be simulated in virtual reality to mimic the real scenario. These scenarios can help you understand all of the local factors that can affect the operation of the wind farm in depth. The virtual solutions lab (VSL) can carry out any high-level work/process simulation. For example, technicians can pre-train in VSL to identify the level of risk during the construction phase or O&M activities.

Figure 4-11. VR glasses example

VR is not a new technology; it has been around since the late 1960s. However, acceptance of this technology is highly dependent on specific market conditions, requirements, and maturity level. According to a report by the United Nations Industrial Development Organisation (UNIDO), the wind industry is entering the fourth industrial revolution [39]. In which VR is one of the next cutting-edge technologies that could solve the current wind energy industry challenges. VR technology has proven to be a game changer for the offshore wind industry in terms of optimizing technician workflow and improving HSE levels through pre-training in VR simulation.

4.3.2.2 Virtual Solutions Lab (VSL)

Through VR-based pretraining for offshore wind energy, Virtual Solutions Lab is assisting in the improvement of technician performance. The primary goal of the VSL is to visualize the wind turbine's Digital Twin model in a virtual environment using VR devices and to conduct a pre-training course in a VR simulator. For example, O&M workflow optimisation, HSE pre-training, structure degradation modelling, the design review process, and so on.

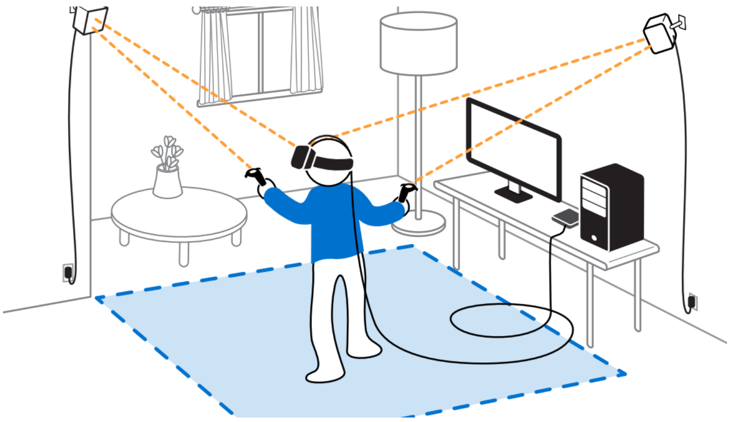

Figure 4-12. Virtual Solution Lab (VSL) concept.

The goal in the COREWIND project is to create a new VR solution for visualizing complex floating offshore wind turbine structures in a more realistic and interactive way during the design phase and in-service. As project deliverables, VR models can be demonstrated as an advanced communication solution with stakeholders as well as a "new way of working" during team and client meetings, workshops, and so on.

Figure 4-12 depicts the three main components of the VSL equipment: VR glasses, a high-end computer, and a projection screen. VSL equipment varies depending on the use-case and user requirements. The fundamental characteristics of VSL hardware and software should be user-friendly, adaptable, and well-known in the VR industry. They should also meet the minimum technical requirements, such as the number of users who can access the license at the same time, the frequency with which new software versions are released, access to supporting toolkits, etc. [40] contains more information on Ramboll's Virtual Solutions Lab concept.

4.3.3 Developed Digital Twins

An example of model calibration can be found in [41] and an example of model updating is presented in [42], where it is explained how a number of tests were performed on a vertical axis wind turbine to ensure the Digital Twin finite element models correctly match the reality. Figure 4-13 illustrates the frequency response functions (FRF) of the experiment.

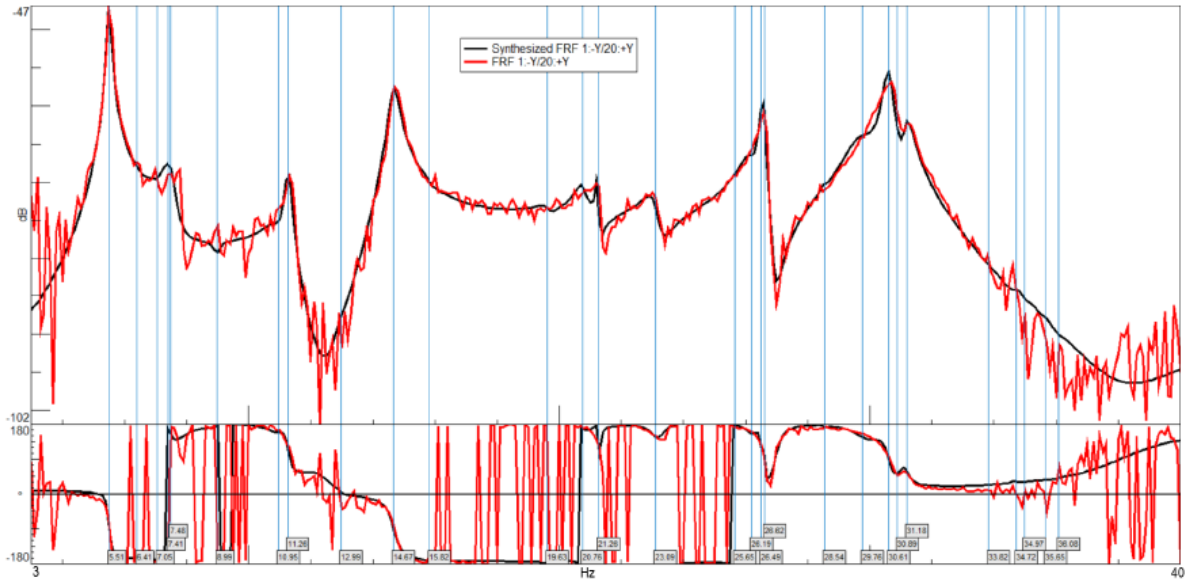

Figure 4-13. Comparison between a synthesised FRF (black) and a measured FRF (red) from the fit mode shapes (blue) [42].

A Digital Twin of an onshore wind turbine was developed using monitoring data [43]. Figure 4-14 shows the bending moments on the tower section, where strain gauges were placed to measure the magnitude.

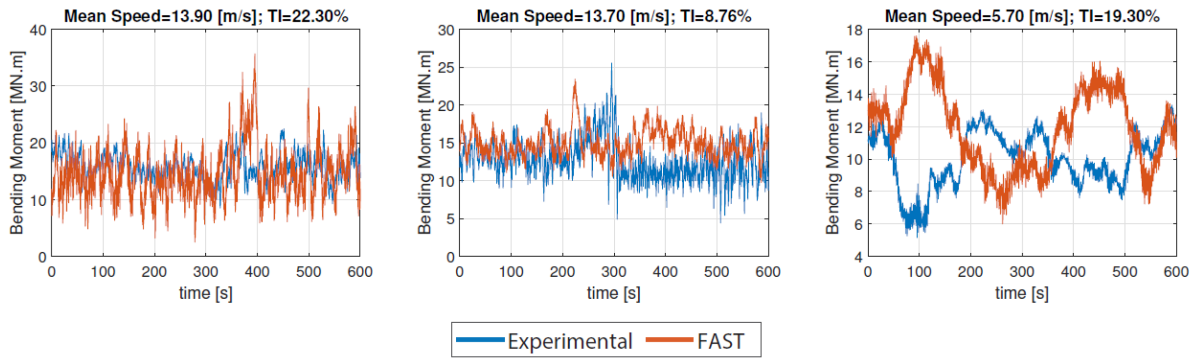

Figure 4-14. Comparison between modelled and measured bending moment [43].

A Digital Twin of an offshore bottom-fixed and floating wind turbine power converter was developed [44]. The 5 MW NREL virtual wind turbine and the wind profiles were imported in a FAST model to generate the torque and speed input parameters of the generator model. Power losses were estimated, as well as the IGBTs and diodes temperature. Figure 4-15 shows how the information provided by a set of virtual sensors located in the structure is converted into useful outputs, including accumulated fatigue damage and failure risk.

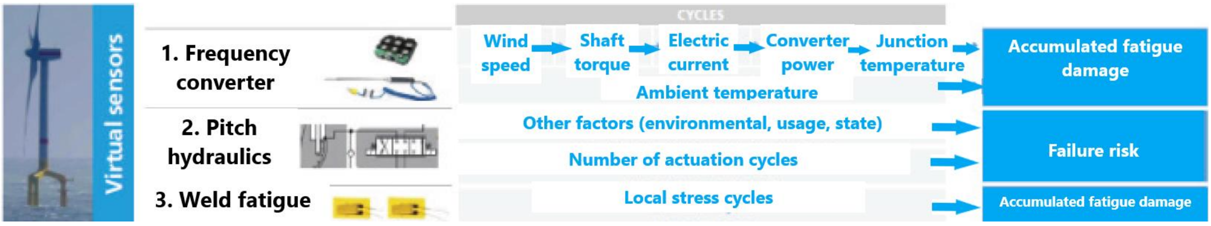

Figure 4-15. Virtual sensors and outputs on a Digital Twin platform [44].

Ramboll has developed "True Digital Twin" (TDT) [45] Digital Twin technologies to create a digital copy of offshore wind assets. The ROMEO project's Digital Twin visualisation tool RamView360 aims to improve understanding of offshore wind farm assets [46]. This ongoing development process of the RamView360 tool is being carried out as part of the COREWIND project, with the scope of development being expanded to include floating offshore wind turbine models.

4.4 BIM-based toolboxes

Building Information Modelling (BIM) is a process to generate and operate a digital model of a physical asset. A BIM model can be considered as a repository of project data that combines technology, people and processes. It contains the physical information of the objects, their hardware and their locations. BIM is widely used in a variety of industries, including civil engineering, plant technology, architecture, the energy sector, and railway construction as it allows a wide control and knowledge of the whole development from an early stage of the project. BIM ensures significant changes in modern industries, transforming their approach to asset maintenance and operation into a more digital one. This processes can equally be applied to the floating wind sector.

4.4.1 BIM concept

BIM (Building Information Modelling) is a process for creating and managing a digital 3D model of a physical asset/system with overlaid information. According to the ISO 19650 standard described in the British Standards Institution (BSI), BIM can be defined as the following:

> *"Building information modelling (BIM) is about getting benefit through better specification and delivery of just the right amount of information concerning the design, construction, operation and maintenance of buildings and infrastructure, using appropriate technologies." [47]*

Simply put, BIM is a method of presenting asset information that is integrated with a 3D visualisation model. Figure 4-16 depicts a BIM example. This diagram depicts how BIM models differ from standard 2D or 3D CAD models. 2D models are a traditional method of working on paper-based communication, whereas 3D models offer more user interactive functionalities. While a BIM model displays a more sophisticated 3D model with asset information overlaid, a CAD model does not. As a result, users can access and track information more easily with BIM models than with traditional 2D and 3D modelling. This BIM technique can be used to create a Digital Twin model.

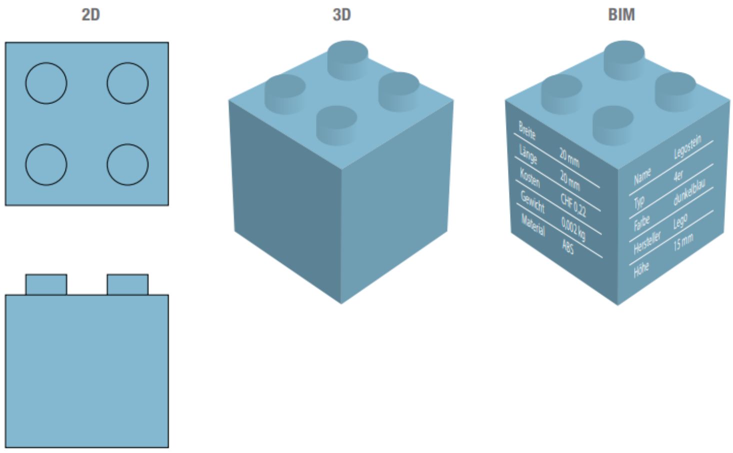

Figure 4-16 The Lego analogy: from 2D CAD to object-oriented Modelling with BIM [48].

According to Zita Sampaio, A. [49], BIM methodology can be combined with VR to visualize the Digital Twin model on a larger scale. The visual stimulation of the building simulation or workflow process is provided by the 4D level BIM model. This simulation process can be used in conjunction with virtual reality to observe the real work planning approach. Advanced BIM models include information data such as economic evaluation, material requirements, sustainability studies, maintenance activities, and so on. The BIM model can be used during all phases of the asset life cycle, including development, commissioning and installation, operation, and decommissioning.

BIM uses smart built environment (SBE) technology, which refers to an environment embedded in smart objects such sensors and actuators that allows interactions. Applying it to the floating wind industry could facilitate the monitoring and diagnosis processes because it includes the information generated from the design to decommissioning in a single model.

A BIM model includes a variable number of dimensions depending on the information it contains:

- 3D – three-dimensional representation of all components.
- 4D – construction planning.
- 5D – costs.
- 6D – energy and sustainability indices.
- 7D – operation and maintenance data.

Figure 4-17 shows the BIM models classification according to their level of detail and maturity. The current status of the floating offshore wind industry is level 1.

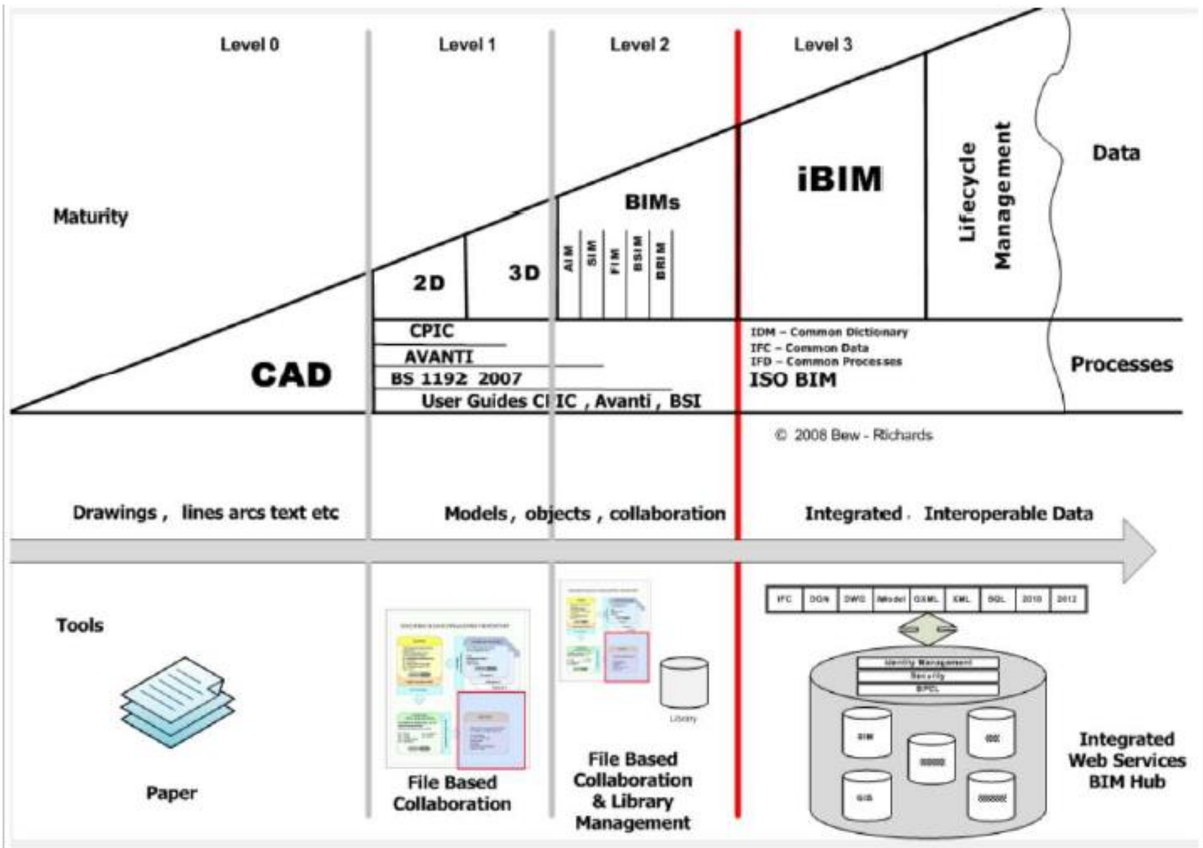

Figure 4-17. BIM levels [36].

4.4.2 Developed BIM models

Most of the relevant research conducted on BIM is not related to the wind technology, but it serves as a reference of what could be done. For example, it was conducted the energy management and analysis of a house that included distributed energy resources, smart meters, actuators and sensors [50]. The integration of sensors to enhance the visualisation of structural health monitoring though BIM was also conducted in [51]. One of the few BIM works related to the wind industry was the design of a prefabricated wind turbine tower [52].

4.4.3 BIM visualisation

Because of the complexity of service providers and contractors working on the same projects, BIM visualisation is common in the building and construction industry. The BIM methodology is new to the wind energy sector, but it has the potential to solve a number of problems [53].

A real-time rendering process, as mentioned by Johansson, M. [54], can reduce the time required to generate and update the BIM model. This enables the offshore wind industry to effectively visualize the BIM model. To share asset information, the OFW industry currently uses file-based collaboration such as 2D CAD drawings, documents, datasheets, and in some cases 3D models. This process can be improved by employing BIM methodology to collect, store, and share information among stakeholders.

However real-time rendering requires real-time access to a large model, and significant computation to continually re-render it as the user moves around. Typically, the user must also install software. By contrast, RamView360 provides a reduced but adequate set of "pre-calculated" renders, much like Google Street View's photographs. This reduces bandwidth and eliminates rendering computations at the point of use.

The BIM application can be expanded to include life cycle management for offshore wind farms. Jia, J., et al. [55] describe how BIM application frameworks can optimize workflow in the virtual environment through the implementation of real scenarios, resulting in an improvement in safety standard, cost optimisation, automatic monitoring, better decision-making process, and so on. As a result, BIM implementation can digitalize the work process and create a fully digital system.

There are tools that provide a BIM environment to visualize BIM models, such as RamView360. This tool provides a 360-degree view from a number of points defined in an offshore wind farm in a 3D environment. Furthermore, technical information related to the components can be accessed and displayed as overlaid data [36]. Figure 4-18 shows an example on how the information is accessed inside the 3D virtual model.

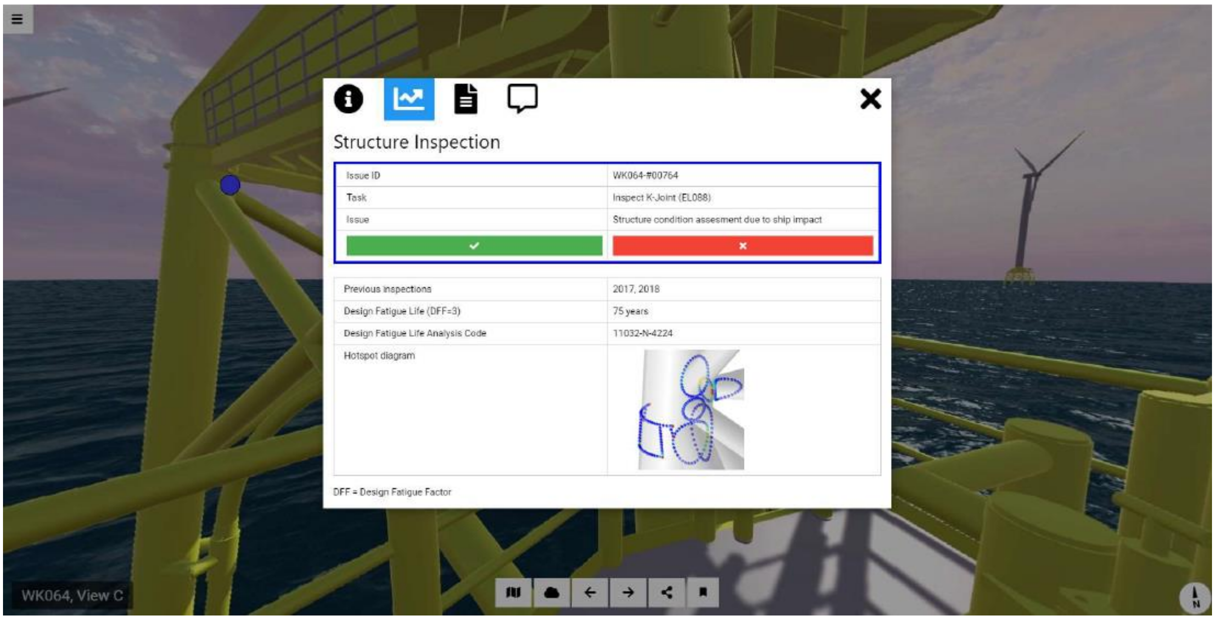

Figure 4-18. Structure inspection in RamView360 [36].

RamView360 [56] is a web-based visualizing tool developed by Ramboll, which can be used for interacting with the Digital Twin model of a system. RamView360 provides a 360-degree view from the specified viewing location in the 3D environment. This tool gives a wide range of functions to visualize the BIM model as per user requirements e.g. BIM visualizer, CFD simulation model, CAD model and point cloud model generated from LiDAR scanning. (LiDAR is a remote sensing method that uses laser light in the form of a pulsed laser to scan the physical object and generates a point-cloud model of the object.) RamView360 uses 360-degree photos from detailed 3D modelling software or point-cloud dataset from the LiDAR scanner. RamView360 uses the BIM method to represent the 3D model with overlaid technical information like component's RDS-PP code, MTBF, MTTR, documents O&M manuals, HSE guideline file, weather data, water depth and temperature measured by sensors, etc. The BIM approach provides user-friendly navigation to find specific information in the Digital Twin model.

Ramview360 tool is easily operated through any web-browser on a computer/tablet/phone. No additional plug-in or software installation is needed. Due to its low bandwidth data requirement, the BIM model can swiftly load and operates very fast compared to traditional comparable software. RamView360 is also compatible with VR glasses or VR cardboard [57] setup (a mobile enable VR glasses made from paper/box material). RamView360 model can easily be shared through the URL sharing function available from the quick access panel in the tool. RamView360 is also capable of communicating data through software API connection with Ramboll's internal web interface and/or any external software applications. RamView360 can be configured as per the customers' requirements. A screenshot of the RamView360 user panel with an example boiler room CFD model is shown in Figure 4-19. For more information and examples can be found on RamView360's official webpage [56].

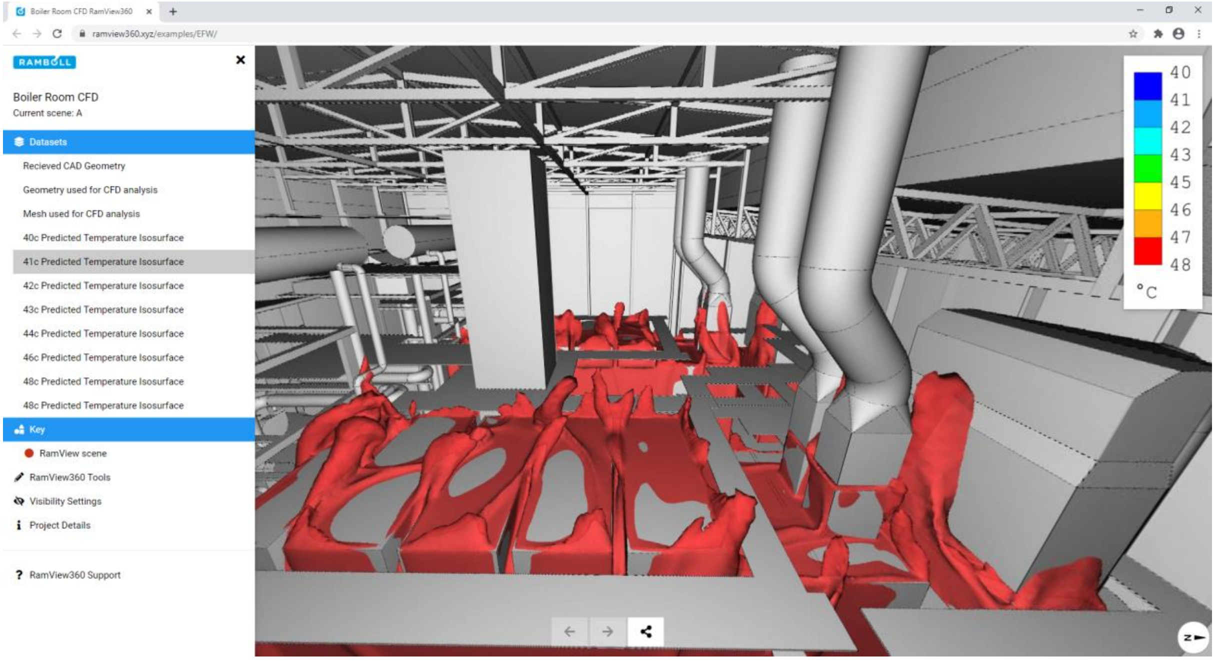

Figure 4-19. RamView360 example Boiler Room CFD [56].

The RamView360 tool has a variety of functionalities for visualizing the Digital Twin model in a 3D environment with informational data overlaid, applicable to offshore wind turbines. Users can interact with the RamView360 tool via various user-interaction platforms such as office computer devices, remote tablet/smartphone, and VR glasses in VSL.

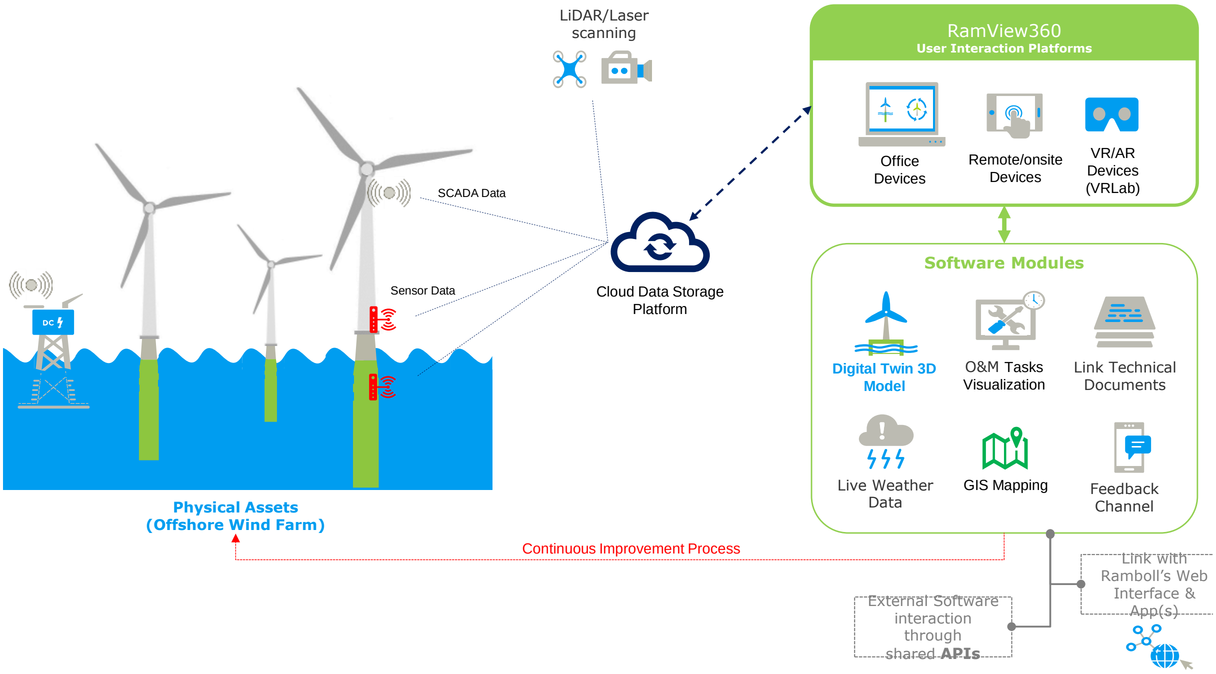

Figure 4-20 Feature of RamView360 Tool

Ramview360 has six basic integrated software modules [46] to establish the generic function of the tool. Additional software modules can be integrated into RamView360 tool according to user specification & requirement. The detailed description of those six modules are as following:

- Digital Twin 3D Model: This module helps to create Digital Twin model in a 3D environment. It uses 360-degree photos as an input and creates a walkthrough virtual environment to visualize the digital copy of physical assets.
- O&M Tasks Visualisation: This module is used to visualize the list of O&M tasks and the status of each specific WTG component. This module can import data from external maintenance management software and integrates it into the Digital Twin 3D model.
- Link Technical Documents: Through this module, the user can easily link technical documents with the specific component of the Digital Twin model. This function can be helpful for the user to find a specific document more efficiently.
- Live Weather Data: Weather module gives live update information of the wind and wave data of the wind farm site. This module imports real-time weather data from integrated weather forecasting platforms like Windy [58], NDBC [59] or data from on-site weather stations.
- GIS Mapping: Global Information System mapping is used to map the location of the assets. This technology allows linking different data points with the geographical location. E.g. soil modelling, water depth for each WTG, etc.
- Feedback Channel: This channel provides the end-to-end communication between technician and expert by providing a comment and image capture functionality.

If a detailed CAD model is not available, the physical assets of the offshore wind farm can be mapped using LiDAR/laser scanning technology. As shown in Figure 4-20, LiDAR/Laser scanning generates point cloud data, which is then processed to create a 3D model for Digital Twin technology. For RamView360, a cloud-based data storage platform is used to store data collected from scanning, sensors, and other sources. This storage platform serves as the foundation for the RamView360 software modules. Sensor technology is used to continuously monitor the behaviour of physical assets and incorporate the results into the Digital Twin model. According to the use case, SCADA statistics can be linked with RamView360. This information can be used to help the user visualize specific KPIs using an integrated 3D Digital Twin model and customised RamView360 panels. To improve the smooth operation and health of the assets, a continuous improvement process is established. RamView360 can be easily interconnected with Ramboll's web interface (a web-based interface for connecting Ramboll's internal software applications) and/or any external software platform such as a maintenance management system, a document management system, and so on using API connections. The RamView360 tool has a high potential for implementing Digital Twin concepts for wind energy assets due to its advanced functionalities and its use cases can be checked in [46].

4.5 Gaps, needs and challenges

The previous sections show the current status of the digitalisation in the floating wind industry while revealing the needs and further steps required to improve the models as described below.

There is a lack of failures data of offshore wind farms, which applies to bottom-fixed farms and particularly to floating farms. Some of the failures data provided has been assumed to be the same as for onshore turbines, therefore there is some uncertainty. On the other hand, failures on the mooring system have been extracted from the oil and gas technology for the same reason.

Regarding the sensors, there is a need of including them in the offshore farms to obtain more accurate and qualitative data, with special emphasis on the interferences attenuation. Additionally, there is still some uncertainty involving which are the best sensors for each component and purpose and some sensors must be developed to monitor floating wind specific components such as dynamic cables.

The development of Digital Twins applied to floating offshore wind turbines and farms is not yet exploited. It is a relevant task due to the fact that there are significant differences between bottom-fixed and floating technologies and the same assumptions and models cannot be used. Additionally, real data needed to feed the AI models is very limited at this moment. The scope of application of Digital Twins can also be widened developing condition monitoring systems with intelligent machine health management and automated analysis.

One of the main gaps in the current state of the art dynamic models is modelling the dynamic cable. The current state of the art is to model the cable as standalone without attaching it to the FOWT in the multibody simulations. Being able to model the dynamic cable in our state of the art servo-aero-hydro-elastic multibody simulations will help us identify the critical loading points on the cable. This will enhance our understanding, and allow us to design more reliable and efficient dynamic cables. In order to add the cable to the multibody simulation USTUTT is planning to use the state of the art coupling between MoorDyn v2 and SIMPACK introduced in [60]. SIMPACK is a flexible multibody simulation tool, which is capable of modelling not only wind turbines but any multibody system. This makes SIMPACK well suited for testing new capabilities before adding them to the source codes of our wind oriented simulation models. The new version of MoorDyn v2 included the bending stiffness which makes it suitable for modelling dynamic cable [61]. However, this version is not yet coupled to OpenFAST as it is still under development.

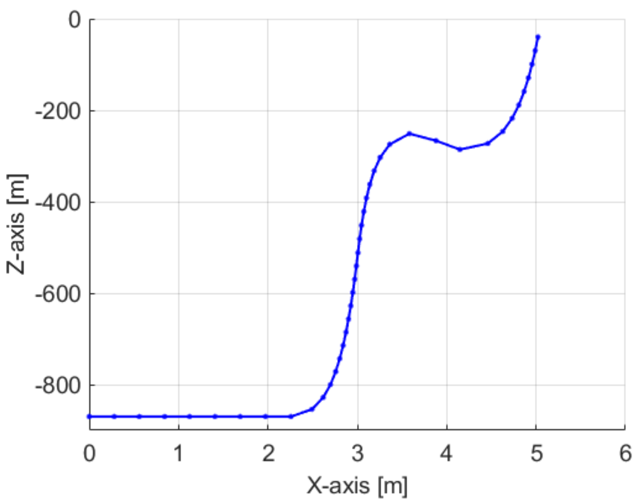

Figure 4-21. Static response of the dynamic cable for Activefloat at Morro Bay.

In Figure 4-21 we show the static response of the dynamic cable for Activefloat site C in Morro Bay. The cable has a total upstretched length of 1200m, and has a lazy wave profile. The figure agrees with the static response extracted from Ocraflex. In the next step we will use the SIMPACK-MoorDyn coupling to calculate the fatigue of the cable. Moreover, we will check if the cable has any effect on the platform's motions.

The current level of BIM applied to the floating wind technology is low and below other technologies. Although it is a complex environment and the BIM integration must include all of its components, the development of advanced BIM models can be done and will provide additional information and a different interaction with the assets. The use-cases of BIM models applied to floating wind are not well defined yet, and should be done in collaboration of all the stakeholders. In this regard, it must be highlighted that BIM capabilities go beyond 3D visualisation.

4.6 Conclusions

The complexity and associated costs of the installation, operation and maintenance of floating offshore wind farms opens the door to deep investments in digitalisation. When it comes to maintenance operations, the quality of the developed virtual models is as important as the physic sensors used to feed them. The advantages of a successful digitalisation include the reduction of unscheduled maintenance activities, early fault detection, quicker repair times, lower dependency on weather windows, reduced installation and operation costs and reduced uncertainties and contingencies. These advantages are achieved by means of online continuous monitoring of relevant variables and virtual models designed to generate valuable outputs that reduce the overall costs and can even increase the energy yield or the assets lifespan.

Knowing which are the typical failures and the available sensors is the first step while defining the variables to be monitored. Next, a digital model can be created, being the most common the Digital Twins and the BIM models. Both models have been described with detail, being a common conclusion that there is still work to do to improve their quality and exploitability.

5 Development and Validation of Open and Agnostic Digital Twin Modules for Floating Offshore Wind

An open-source and agnostic Digital Twin for the floating wind turbine has been developed and is presented in this section. The activities carried out to reach it include the development of modules for behaviour prediction based on machine-learning techniques, from the selected input-outputs, for determining if the system is behaving as expected. This tool enables better diagnosis of performance and contribute to lower the costs, mitigate risks of unplanned system downtimes and increasing reliability.

This development intends to create a Digital Twin for a floating wind turbine. The idea is that the digital model with several measures such as the wind speed, rotor speed, turbine position, and orientation should give the expected power production, tower shear forces, and anchor tensions. The expected outputs are compared with the real field measures, and if it exceeds the acceptable limits, an alert arises to the responsible personnel.

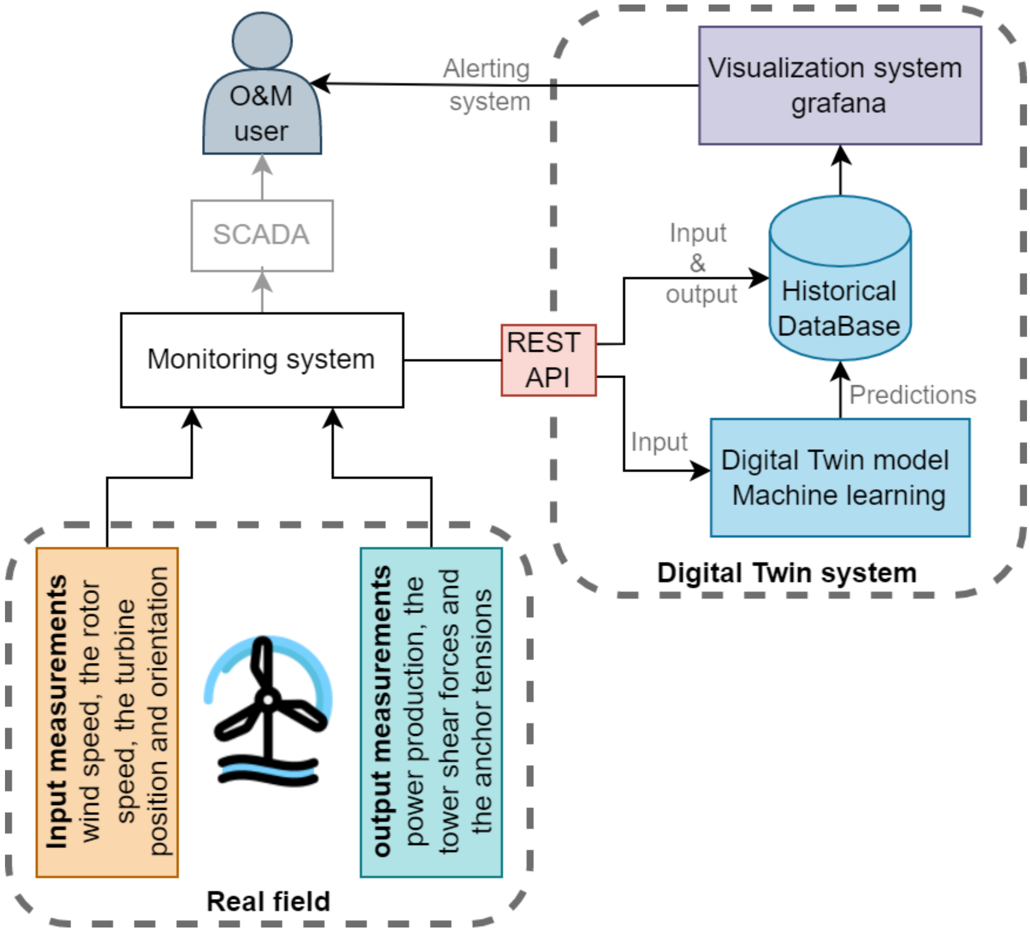

Figure 5-1. Conceptual diagram of the Digital Twin applied to offshore wind turbine.

Figure 5-1 describes the actors and elements in an installation using a Digital Twin. From one side, there is the real field with the wind turbine. The information from the real field is gathered in real-time by the plant supervision system. This data can be divided into two parts: the input and output values for the Digital Twin. When the Digital Twin system receives the data, it stores the data in the database, and also, the machine learning model, with the input data, predicts the expected outputs. Then there is the visualisation part that visually presents the measurements and results and takes part in the alerting system. It alerts if one of the expected values predicted by the model is not in the correct margins.

5.1 Challenges to be dealt with

One of the first challenges faced in this development was that there was no data to train the machine learning model. Then as a solution, we decided to do simulations using the OpenFAST tool [62] to simulate a wind turbine to obtain the data. The simulations were done with the definition made by the IEA Wind TCP Task 37 [63], where there is the definition of a 15 MW offshore wind turbine, with all the physical and electrical models to run in the OpenFAST tool.

Also, using this solution faced an unexpected situation because the tool provides a dynamic simulation, and the first part of the results was not valuable for the training due to the transition. For that, some pre-process was done to obtain steady-state data to be used for the training and another part for the validation.

The other significant challenge was the number of variables and the expected outputs. First, understand each of these variables. The preparation of all these data requires relatively high data processing capacities. Table 5-1 shows all the input and output variables. The different measurements can be divided into the environmental wind and wave measurements, position and angle measurements, and force measurements.

Table 5-1. Inputs and outputs for the machine learning model.

Inputs		Outputs	
Name	**Description**	**Name**	**Description**
Wind1VelX	Horizontal wind speed	TTDspSS	Tower-top / yaw bearing side-to-side (translational) deflection (relative to the undeflected position)
HWindSpeed	Wind speed at hub	OoPDefl1	Blade 1 out-of-plane tip deflection (relative to the pitch axis)
PropagationDir	The direction of wind propagation	IPDefl1	Blade 1 in-plane tip deflection (relative to the pitch axis)
WaveTp	Wave peak period	GenPwr	Power generation
WaveHS	Significant wave height	TwrBsFxt	Tower base fore-aft shear force
WaveDir	Wave direction	TwrBsFyt	Tower base side-to-side shear force
Azimuth	Rotor azimuth angle	ANCHTEN1	Anchor 1 tension
RotSpeed	Rotor rotation speed	ANCHTEN2	Anchor 2 tension
GenSpeed	Generator rotation speed	ANCHTEN3	Anchor 3 tension
PtfmSurge	Platform surge		
PtfmSway	Platform sway		
PtfmHeave	Platform heave		
PtfmRoll	Platform roll		
PtfmPitch	Platform pitch		
PtfmYaw	Platform yaw		
TTDspFA	Tower-top / yaw bearing fore-aft (translational) deflection (relative to the undeflected position)		

In Figure 5-2, there is a description of the steps followed to obtain a valid model for the Digital Twin. As is explained before, the first step is to obtain the data running the simulations of the wind turbine. Then process all the obtained data to delete the transitions and not desired behaviours, and with all of this data, split the data into two parts: one part for the model training and the other for the validation. The third step is to do the machine learning explained in the following chapters. And finally, the last step is to use the model already trained with the validation data to evaluate its behaviour. This fourth step is evaluated using the data like measurements provided from a real installation. Also, the visualisation system is used to monitor the evolution and trigger alerts to the operation and maintenance team.

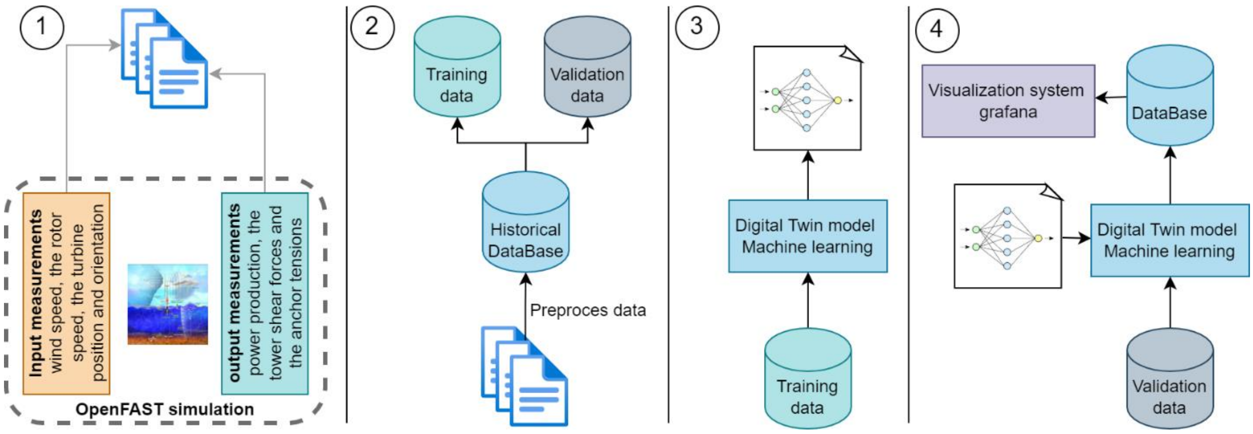

Figure 5-2 steps for the machine learning training and validation.

5.2 Machine Learning algorithm definition

A neuron is the basic unit of the brain; there are roughly 86 billion neurons in the human nervous system, which are linked by 10^{14}-10^{15} synapses. After processing the signal, each neuron gets it from the synapses and outputs it. This concept is derived from the brain in order to construct a neural network.

Each neuron computes the dot product of the inputs and weights, adds biases, applies an activation function, and outputs the results. A neural layer is formed when a large number of neurons work together to produce a large number of outputs. Finally, several layers come together to form a neural network.

Neural networks are produced when many neural layers unite to form a network, or we may say that some layers' outputs are inputs for other layers. The completely connected layer is the most frequent form of layer used to build a basic neural network, in which neighbouring layers are fully linked pairwise, and neurons in a single layer are not coupled to each other.

Conventions for naming. We do not count the input layer in the N-layer neural network. As a result, a single-layer neural network defines a network that contains no hidden layers (input directly mapped to output). In the case of our code, we'll utilise a single-layer neural network, which means there will be no hidden layer.

The output layer is unlike the neurons in the other layers of a Neural Network. The neurons in the output layer almost never have an activation function (or you can think of them as having a linear identity activation function). This is due to the fact that the final output layer is typically used to represent class scores (e.g., in classification), which are arbitrary real-valued values or some type of real-valued objective (e.g. In Regression).

Deep Neural Networks contain so many hyperparameters that it would take too long to examine them all separately, but it should be noted that some parameters directly affect the efficiency of the model: number of hidden layers and their number of neurons, activation function, optimiser and loss parameter.

Input Layer Neurons receive the input information (usually numeric representations of text, image, audio and others types of data), process it through a mathematical function (activation function) and "send" an output to the next layer's neurons based in conditions. On the way to other layer's neurons, that data is multiplied by pre-set weights (placed in the graphical lines linking one neuron to the others).

A hidden layer in an artificial neural network is a layer in between input layers and output layers, where artificial neurons take in a set of weighted inputs and produce an output through an activation function. Hidden neural network layers are set up in many different ways. In some cases, weighted inputs are randomly assigned. In other cases, they are fine-tuned and calibrated through a process called backpropagation.

Within an artificial neural network, a neuron is a mathematical function that model the functioning of a biological neuron. Typically, a neuron computes the weighted average of its input, and this sum is passed through a nonlinear function, often called the activation function, such as the sigmoid. The output of the neuron can then be sent as input to the neurons of another layer, which could repeat the same computation (weighted sum of the input and transformation with activation function).

The activation function decides whether a neuron should be activated or not by calculating the weighted sum and further adding bias with it. The purpose of the activation function is to introduce non-linearity into the output of a neuron. We are using sigmoid and rectified linear activation functions.

Optimisers are algorithms or methods used to minimise an error function (loss function) or maximise production efficiency. Optimisers are mathematical functions dependent on the model's learnable parameters i.e. Weights & Biases. Optimisers help to know how to change weights and learning rate of neural network to reduce the losses.

The loss function in a neural network quantifies the difference between the expected outcome and the outcome produced by the machine learning model. From the loss function, we can derive the gradients which are used to update the weights. The average overall losses constitute the cost.

5.3 Model development and validation

If we were working on classification problem, there are two main indicators that we should look at; accuracy and validation loss values. But when doing Regression, the situation is a little more complicated because each parameter draws attention to a different issue and actually directly affects the performance of the model. So even if the prediction results of our model are very good, if the error rates are high or inconsistent, it may mean overfitting or that the model is not good enough. For all these reasons, in this section we will look at the 3 main error values and the prediction results.

Mean Absolute Error (MAE): In the context of machine learning, absolute error refers to the magnitude of difference between the prediction of observation and the true value of that observation. MAE serves as an easy-to-understand quantifiable measurement of errors for regression problems.

Mean Squared Error: MSE is the average of the squared error that is used as the loss function for least squares regression. The mean squared error of a model with respect to a test set is the mean of the squared prediction errors over all instances in the test set

Root Mean Squared Error: It tells you how concentrated the data is around the line of best fit. Root mean square error is commonly used in climatology, forecasting, and regression analysis to verify experimental results.

Since we have a very large data set, it will be useful to connect the variables with each other and create a similarity within itself with the pre-operation. Because many machine learning algorithms perform better or converge faster when features are on a relatively similar scale and/or close to the normal distribution. In this research we chose Min-Max Scaler. For each value in a feature, Min-Max Scaler Min-Max Scaler subtracts the minimum value in the feature and then divides by the range. The range is the difference between the original maximum and original minimum.

The variables we use to navigate our model and their relationships with each other are as shown in the correlation matrix in Figure 5-3. A correlation matrix is a table showing correlation coefficients between variables. Each cell in the table shows the correlation between two variables.

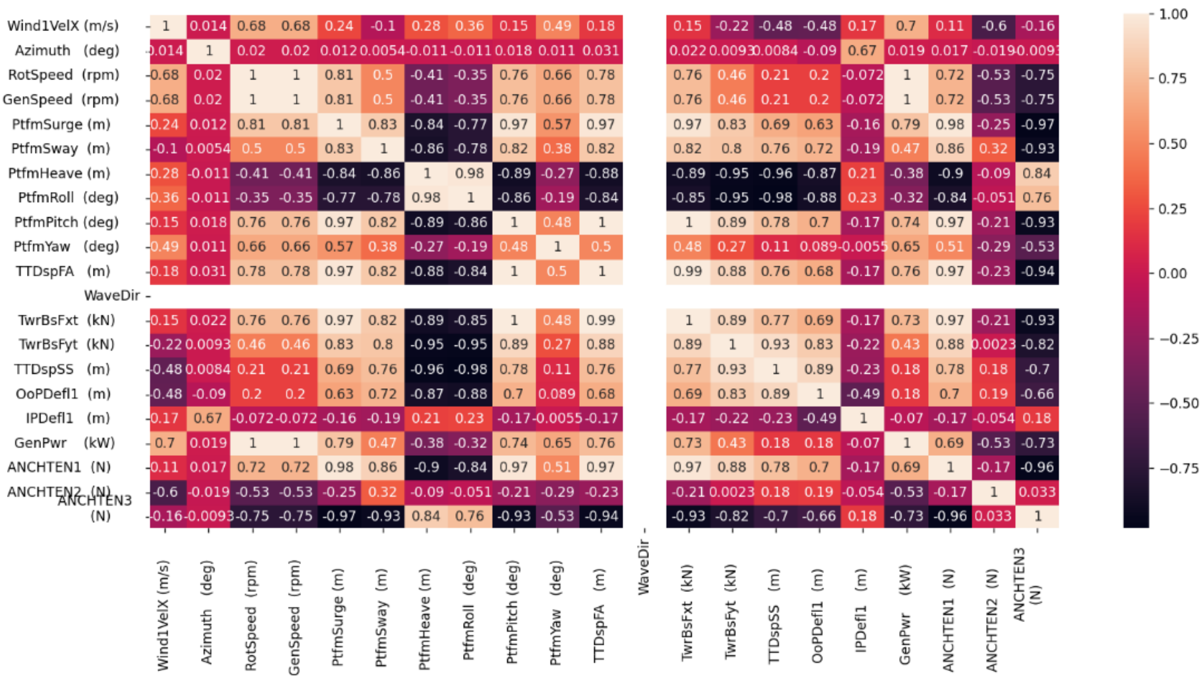

Figure 5-3. Correlation matrix.

The hyperparameters we explained above were updated, and the most efficient model was tried to be created. In the light of the error rates, correlation of variables and time efficiency, it was shaped as shown in Table 5-2.

Table 5-2. Model: "sequential"

Layer (type)	Output Shape	Parameters
dense (Dense)	(None, 128)	2176 (Input Layer)
dense_1 (Dense)	(None, 256)	33024 (Hidden Layer)
dense_2 (Dense)	(None, 256)	65792 (Hidden Layer)
dense_3 (Dense)	(None, 128)	32896 (Hidden Layer)
dense_4 (Dense)	(None, 9)	1161 (Output Layer)

Total parameters: 135,049; trainable parameters: 135,049; non-trainable parameters: 0.

```
dense_4 (Dense)              (None, 9)                 1161
=================================================================
Total params: 85,769
Trainable params: 85,769
Non-trainable params: 0
_________________________________________________________________
mean_absolute_error: 0.58%
MSE:0.00, RMSE:0.02
Training Set R-Square= 0.9873799773290816
```

Figure 5-4. Training Results of our Regression Model.

After reaching the model's optimum parameters, we can see that the error rates became like in Figure 5-4. R-Squared is a statistical measure of fit that indicates how much the independent variables explain the variation of a dependent variable in a regression model. For example, an R-squared of 100% means that all movements of other dependent variables are entirely explained by movements in the index (or the independent variables), and in our code, we almost reach 100, so we can say that the parameters we choose fit well for our regression model. Also, MSE, MAE, and RMSE results show that the model predicts very good but not overfitting with the dataset.

The error values of some variables can be seen in the figures below. The values shown in these graphs are formed as follows: The absolute value of the difference is taken by subtracting the actual value from the prediction made by the regression model. It should not be forgotten that these values are taken from the Min-Max Scaler.

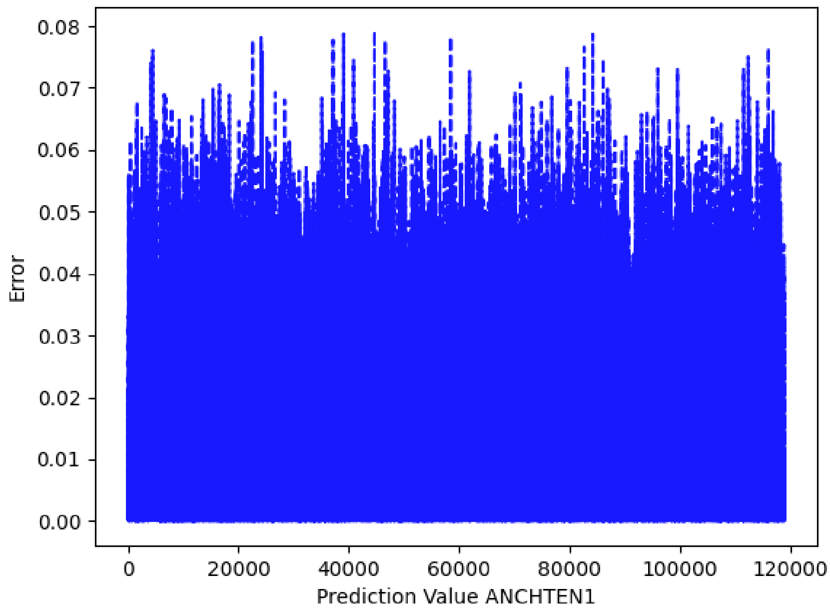

Figure 5-5. Error value of the anchor tension 1 parameter.

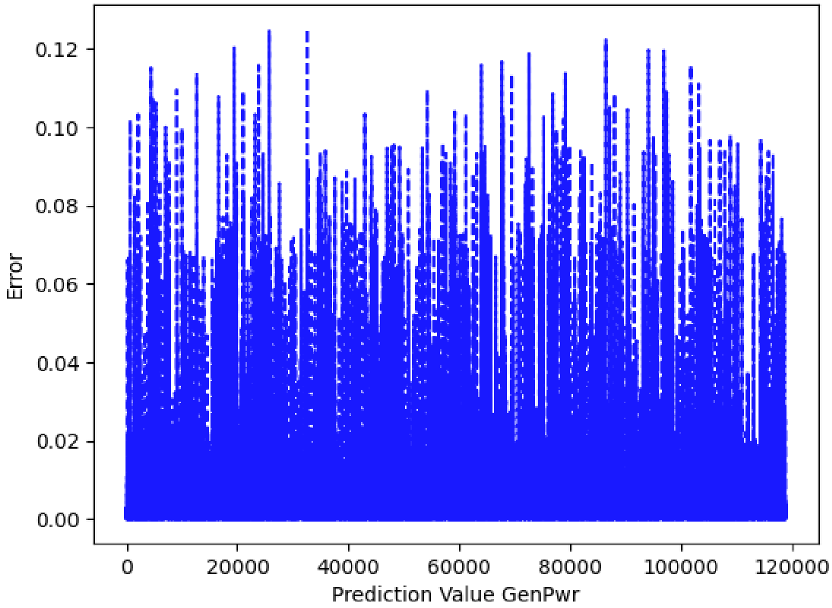

Figure 5-6. Error value of the generator power parameter.

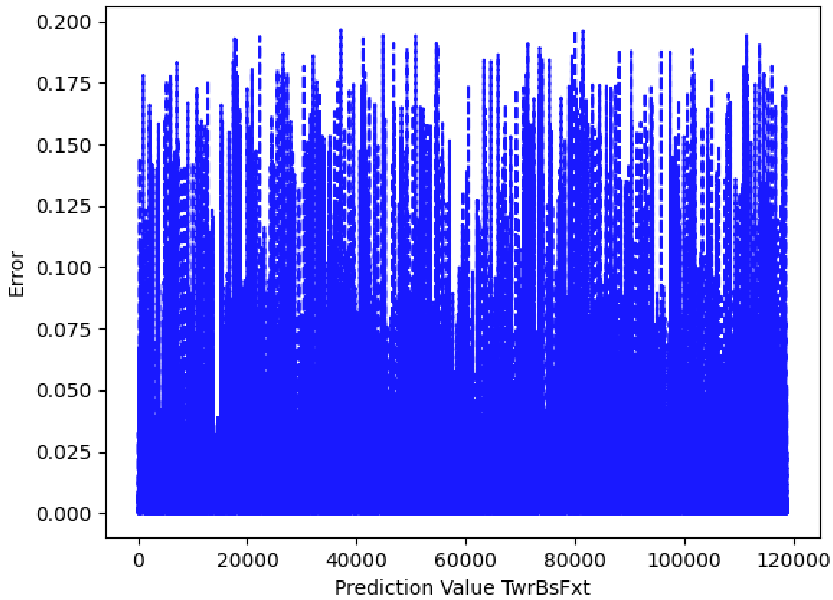

Figure 5-7. Error value of the tower base fore-aft shear force parameter.

5.4 Graphical Interface for real integration

The tool has been designed to allow multiple installations. The tool comprises several containers exploiting the Docker containers technology, where the tool is based on microservices [64]. In Figure 5-8, there is the tool's architecture, where a REST API will handle the information from the different installations and, depending on the action, will be sent directly to the database or the machine learning model. The designed architecture allows high availability of machine learning services, running more or fewer containers depending on the petitions of the system. The RabbitMQ [65] manages a queue where the system starts a new machine learning container if the others are busy. All of the containers have a connection with the database to store all the information.

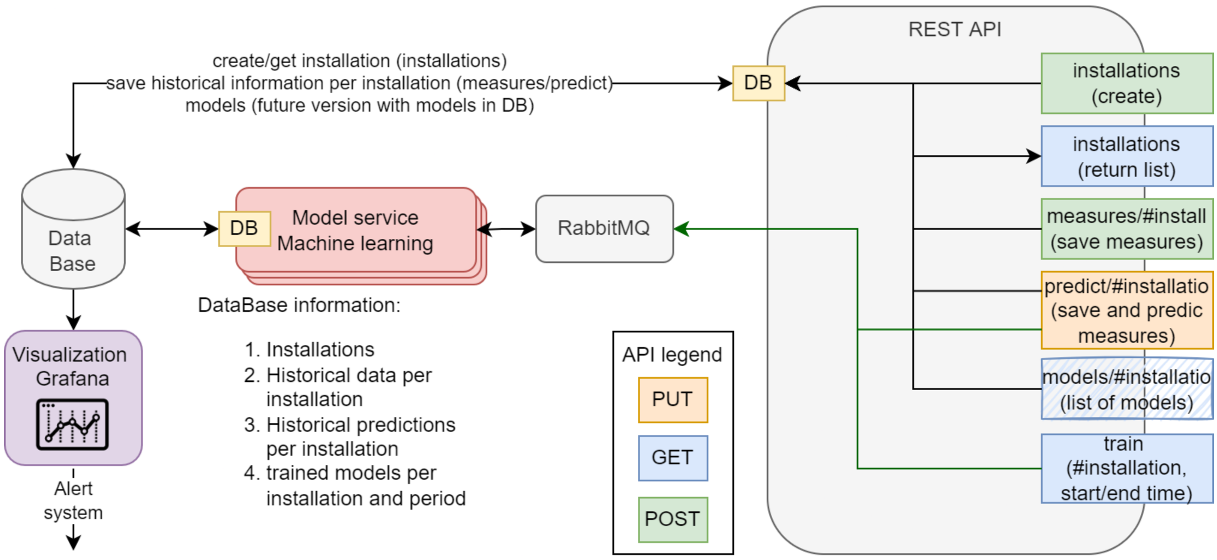

Figure 5-8. Digital Twin architecture.

The visualisation is in charge of Grafana [66] dashboard open-source analytics and visualisation web application that can send alerts via different methods like emails or more new technologies like Telegram. All the input and output variables are displayed on the web page. Furthermore, the output variables are compared with the real measures on the system, and another chat displays the difference and the acceptable configurable limits. Also, the alerting section on the website allows configuring the alarms and the method used to notify the alarms.

Figure 5-9. Example of the visualisation platform developed for the digital twin.

5.5 Conclusions

In this chapter, the Digital Twin approach using machine learning has been explained. From the Digital Twin concept to the development and validation has been explained. Also, has been explained the challenges faced on this development, principally the lack of data and the huge amount of information needed. Then there is the explanation about the machine learning method used and its validation. And finally, the final architecture and its visualisation and alerting system are defined.

6 Model Based Control and Operation for Life-Extension Floating Offshore Wind

In this section, the development of advanced control strategies for extending the life of the equipment and the wind farm is presented. Taking advantage of advanced knowledge and physical-equations, for determining the state of health of the equipment and adapting the controllers accordingly to diminish the stresses.

6.1 Challenge to be dealt with

Typically, wind turbines operate in a "greedy" mode. This means that each wind turbine is always trying to extract the maximum and operate in its optimal point according to the wind reaching the wind turbine. It must be understood that it is possible that providing a holistic wind farm perspective the energy or operation of the whole system may be optimised.

In this regard, due to the large penetration of renewables, some Transmission System Operators (TSOs) indicate the exact amount of power/energy to be delivered by the Wind Farm; which can be lower than the maximum available. Taking into consideration such potential curtailment, there is some degree of freedom to decide how to deliver such power since there is no need to ensure that all turbines operate at optimal point. Thus, such "flexibility" is of use for several actions as energy reserve optimisation, or load reduction.

Additionally, there is the need of increase the life-time of equipment, in order to make it cost-efficient and sustainable. In order to do so, from the wind turbine (and floating wind turbine) perspective there is the need to reduce the mechanical loads which lead to degradation of the components including turbine, tower, floater, etc. Additionally, traditional wind farm operation creates uneven loads on the turbines, leading to a reduced lifetime of some wind turbines.

So, an initial challenge to handle is how to optimize the control of the wind farm to reduce and optimize the loads of each wind turbines and another problem is to include the floater dynamics on the global and conventional dynamic of wind turbines.

6.2 Modelling procedure

One of the most critical steps for developing accurate and effective controllers is to define and model the plant properly. In this regard, common models of floating wind turbines are highly complex which makes it difficult to handle and develop controllers. Additionally, complex systems (detailed models) involve a high order plants, large amount of non-linearities which are required to better understand real behaviour but not needed for control design, since the most relevant dynamics are the dominant and the ones required to be considered.

In this line, the modelling and physical-based equations considered for a proper evaluation and treatment of floating wind turbine fatigue status and sources of loads are presented. In this regard, offshore and especially floating wind turbines are impacted by both varying time-dependent aerodynamic and hydrodynamic loads, which cause fatigue to the components.

Next, the most relevant aspects for the control strategy will be mentioned, although [P2] can be consulted where the results were presented, containing the necessary and more detailed equations of its execution. As seen in the scheme of Figure 6-1, the main forces in the structure can be observed, being the main forces, hydrodynamic and aerodynamic and the main moments those of the tower-base, the moments of the blades and the moments of the shaft. Due to the spar base structure is used, and it is assumed that the structure does not have a significant effect on the waves, the hydrodynamic loading on the submerged structure can be computed via the Morison's equation:

$$dF_h = \rho_w \frac{\pi}{4} D^2 (C_M \dot{v_r} + \dot{v_w}) dz + \rho_w \frac{\pi}{2} D^2 C_D v_r |v_r| dz$$

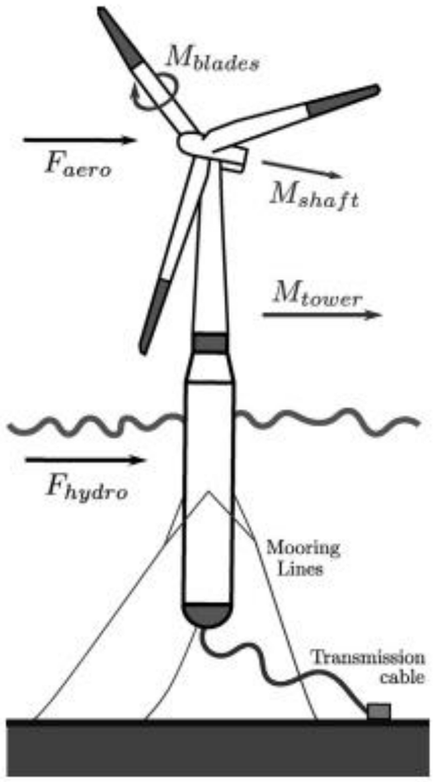

Figure 6-1. Forces on a Spar Structure. From [P2].

being dF_h the horizontal force on a vertical element of the cylinder (at level z), ρ_w the sea water density, D the tower outer diameter and C_D and C_M the drag coefficient and the added mass coefficient, respectively. The variables v_r and $\dot{v_r}$ represent the relative velocity and acceleration between body (v_b) and undisturbed water particles (v_w). By integrating throughout the length of submerged structure respect to the mean water level, the resulting positive sign force is assumed on the wave propagation direction and moment are obtained. In the aerodynamic aspect, the kinetic energy in the wind flow field is harvested by the rotor turbine and transformed into mechanical power expressed as:

$$P_a = \frac{1}{2}\rho A v^3 C_p(\lambda, \beta)$$

producing an aerodynamic force:

$$F_a = \frac{1}{2}\rho A v^2 C_T(\lambda, \beta)$$

being ρ is the air density, A the rotor disc area, v the effective wind speed on the rotor and C_T represent the thrust coefficient, which depends on pitch angle β and λ, the ratio of the tip speed of the turbine blades to wind speed. As the shaft bending moment is related to the torque exerted on the low-speed rotor shaft, let us express it in terms of the mechanical power as:

$$M_s = n_g \frac{P_a}{\omega_R}$$

being n_g the gearbox ratio of the wind generator.

Next, to obtain an effective control strategy, the wake effect that occurs in long wind farms must be considered, since the wake effect, the position of the i^{th} turbine and the power references of the other wind turbines will influence the wind speed of each turbine v_i and, therefore, its available power, leading to substantial power losses. Despite there are different wake effect models, most are based on the Jensen/Park model, which propose a linear expansion of the wake considering the balance of momentum and the wind speed deficit evaluated by the turbine thrust coefficient. By analysing Figure 6-2 and considering that, due to the superposition the total wake effect is the sum of single wake effects, the wind interfaced by the i^{th} FOWT, can be modelled as:

$$v_i = v_n \left(1 - \sum_{j \in N_i} \left(1 - \sqrt{1 - C_T}\right) \left(\frac{R}{s_k}\right)^2 \frac{A_{S,i}}{A_{0,i}}\right)$$

being

$$A_{S,i} = s_k^2 \, cos^{-1}\left(\frac{L_{i,j}}{s_k}\right) + R^2 cos^{-1}\left(\frac{d_{i,j} - L_{i,j}}{s_k}\right) + d_{i,j} z_{i,j}$$

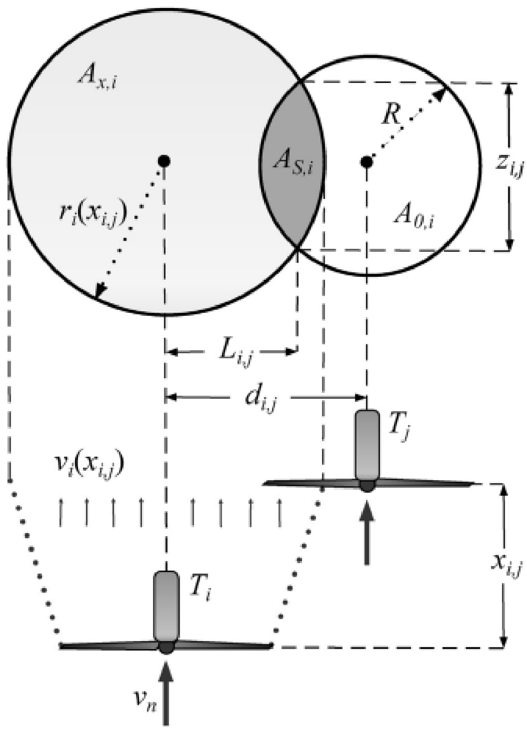

Figure 6-2. Wind turbine wake effect. From [P2].

6.3 Control definition

The main objective of the developed controller must be follow the wind farm power reference while distributing the power in the wind farm such as every turbine suffers the same amount of the loads. For that, a hierarchical non-centralised model predictive control to ensure the correct power and fatigue loads distribution in a WF, depicted in Figure 6-3 was developed. Basically, taking $j = (j_1, \dots, j_m)$ as the cluster index, and $i = (i_1, \dots, i_n)$ as the number of wind turbines in each cluster, the N^{th} wind turbine can be denoted as $N_{j,i} = (N_{j,1}, \dots, N_{j,n})$, and its specific fatigue status as $S_F^{N_{j,i}}(M_{tb}, M_s)$.

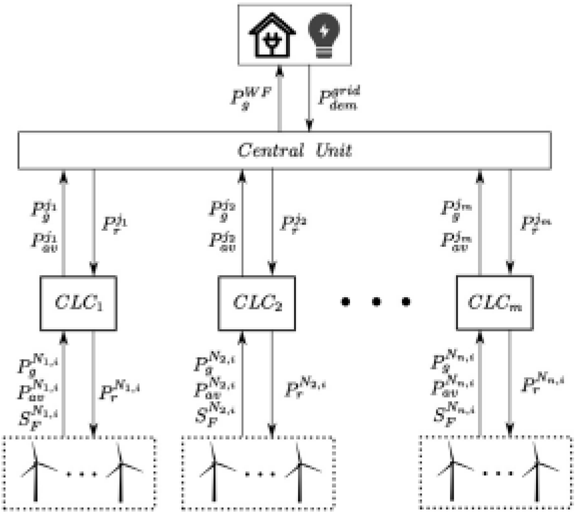

Figure 6-3. Control Scheme proposed to be applied. From [P2].

Starting with the Central Unit (CUC) controller, the MPC strategy can be defined as:

$$\min_{u_p(k)} \sum_{k=1}^{N_p} \delta_\beta J_\beta\big(x_p(k), \Delta u_p(k)\big)$$

$$s.t. \qquad u_p^{min} \le u_p(k) \le u_p^{max}$$

$$J_{\beta,1} = \left\| x_p(k) \right\|_{\delta_{\beta,1}}^2$$

$$J_{\beta,2} = \left\| \Delta u_p(k) \right\|_{\delta_{\beta,2}}^2$$

Being the control matrix u_p formed by the reference powers delivered to each cluster and the states matrix $x_p = \left[\Delta P_g^j , \epsilon_P\right]^T$. This higher level control ensures wind farm power delivery to the grid, i.e. $P_g^{WF} = P_{dem}^{grid}$. By receiving from the j^{th} CLC, the generated P_g^j and available P_{av}^j powers, the control sets an optimal distribution of new power references P_r^j in order to satisfy the demand. Following with the CLCs (Cluster Level Controllers) the goal is to distribute the required power P_r^N set-points taking care on the turbines fatigue status, while trying to minimize the power tracking error, so the MPC strategy is expressed as:

$$\min_{u_c(k)} \sum_{k=1}^{N_p} \lambda_d J_d(x_c(k), u_c(k))$$

$$s.t. \begin{cases} u_c^{min} \le u_c(k) \le u_c^{max} \\ S_F^{N_{j,i}}(k) \le S_F^{max}, \qquad i = 1, \dots, n \end{cases}$$

The cost function J_d enclose three objectives. The first $J_{d,1}$ reduce the power reference tracking error imposed by the central control unit. The second $J_{d,2}$ is to penalize the turbines with a higher accumulated fatigue ratio and the last $J_{d,3}$ is imposed due to the need to protect the turbine from possible damage originating from the controller.

$$
\begin{aligned}
J_{d,1} &= \left\| P_r^j - \sum_{i=1}^{n} P_g^{N j,i} \right\|_{\lambda_{d,1}}^2 \\
J_{d,2} &= \left\| 1 - \left(S_F^{N j,i}(k) - \frac{1}{i} \sum_{i=1}^{n} S_F^{N j,i} \right)^{\xi} u_c(k) \right\|_{\lambda_{d,2}}^2 \\
J_{d,3} &= \| \Delta u_c(k) \|_{\lambda_{d,3}}^2
\end{aligned}
$$

6.4 Simulation and Results

Two control strategies are presented: on based on maximising the power and a second strategy based on the fatigue states. To perform a comparison between controls, a same scenario is proposed for both. During the first seconds, the operation is considered close to the maximum (allowed by wind flow), and the turbines produce a power close to the maximum available power ($P_g^{Nj} \approx P_{av,max}^{Nj}$) so that no other possible combination could supply the power required by the central unit. Later, to verify the operation of the control strategy, decrease in demand is produced. To perform a fair comparative, two hierarchical control strategies are presented. The first, maximizing power through maximizing available power and the results are shown in Figure 6-4.

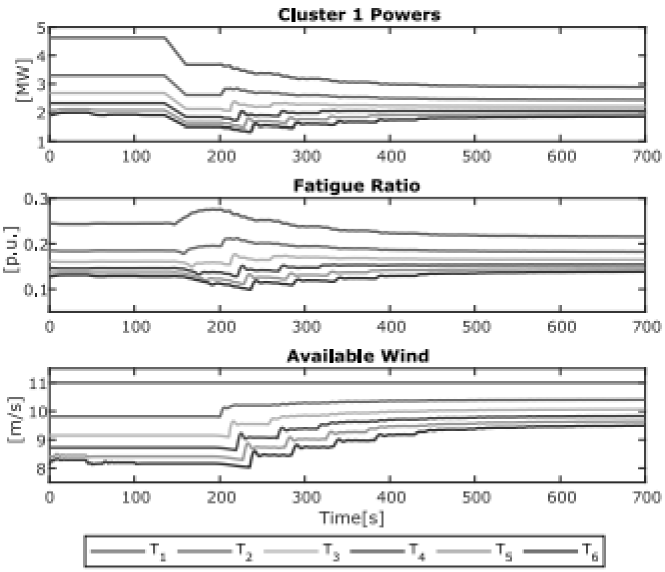

Figure 6-4. Strategy based on maximizing the available power. From [P2].

The second is our proposal, which is based on the turbines fatigue status. The complete analysis of the results can be founded on [P2]. Here, basically can be proved and observed that by comparing both strategies, with the proposed one, the turbines subject to greater fatigue can be reduced by near 25% and the second most affected, by 11% (These values are subject to analysis time, but clearly justify the effect of the controller). Figure 6-6 depicts the numerical comparative.

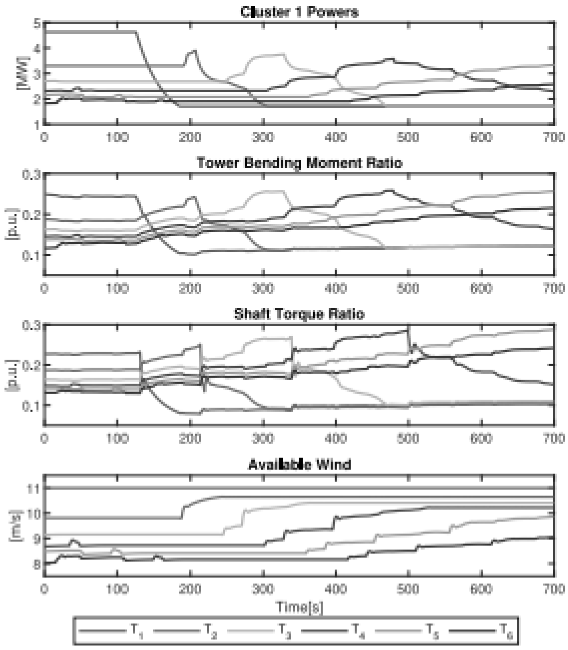

Figure 6-5. Proposed Strategy. From [P2].

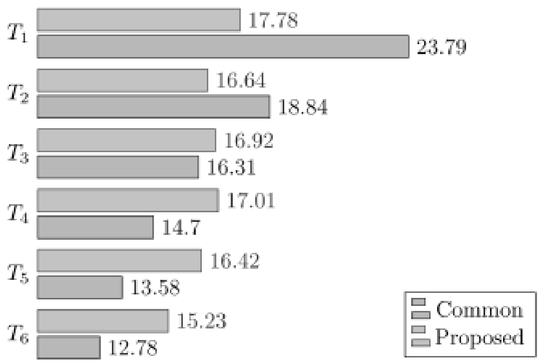

Figure 6-6. Comparative Analysis. From [P2].

6.5 Conclusions

This section has presented an innovative control strategy based on Model-Predictive-Control algorithms (MPC) based on a clusterisation of the floating wind farm for load reduction. The modelling, control architecture developed has been introduced. The controller proposed and presented solves the main problem related to uneven loads distribution, ensuring life-extension of the wind farms, since a reduction of about 25% is achieved (subjected to simulation times). The controller self-adapts depending on loads measurements, leading to a controller and optimised operation of the whole wind-farm; meanwhile being capable of providing the required energy by the grid operator.

7 Development of BIM Models: New Dimensions for a Better Asset Management

7.1 Introduction

The overall goal of this chapter is to create a proof of concept for a lightweight visualisation tool for effective asset management between different WF stakeholders using advanced 3D visualisation technologies such as Virtual Reality (VR)/ Augmented Reality (AR) as a final goal for effective communication and cost optimisation. Virtual reality is poised to become a game-changer in the wind energy industry, particularly in the visualisation of the windfarm Digital Twin model over the course of a wind farm's whole life cycle. In this regard, virtual reality can be an effective technological option for creating a more realistic visualisation model with interactive features. Ramboll is actively working on developing a cutting-edge virtual reality solution for the offshore industry.

In COREWIND project advanced BIM methodology and additional functionalities were developed to modify RamView360 tool further compared to the ROMEO project [46]. In depth a proof of concept BIM model of FOWT was developed in RamView360 to extend the scope of the tool. Ramboll concentrated on demonstrating the BIM visualisation tool RamView360 for effective asset management throughout the life cycle of floating offshore wind farms. The presented visualisation tool use cases demonstration is regarded as a generic showcase for meeting the diverse needs of wind farm stakeholders such as wind farm owners, WTG manufacturers, foundation designers, TSOs, external advisories/government, independent service providers for O&M/construction, and so on. The reference proof of concept floating wind farm Morro Bay is used as a reference site in this document for the development of the Digital Twin 3D model. Due to the lack of CAD models, the scope of this Digital Twin 3D model is limited to the wind turbine foundation. WTG sub-components such as the gearbox, transformer, and so on are not considered.

RamView360 tool was initially started to develop under the EU funded project ROMEO [46]. In this project the basic functionality and concept of the tool was developed. A BIM model of Jacket type foundation was created. In COREWIND project [67], RamView360 Tool is developed further in advance level and many high level BIM functionalities were modified in the tool. Under COREWIND project an exemplary the BIM model of the 15MW class WTG model with floating semi-submersible type foundation was developed.

7.2 Assumptions

In this research project, there is some limitation on the scope of the digital model assumed before starting the research work [46]. Baseline assumptions for the executed work are:

- The research work is focused on (floating) offshore wind industry use-cases.
- The scope of the RamView360 demo model is limited to the main components (Main components: floater, tower, rotor, nacelle, mooring lines, dynamic cable, internal platforms) of the WTG and foundation, while WTG sub-components (e.g. Gearbox, transformer, etc.) and substation models are not considered due to unavailability of detailed CAD/3D model.
- The Morro Bay floating wind farm is considered as a reference wind farm and WTG–11 is considered as the reference WTG for the proof of concept model.
- The demo case-study is concentrated use-cases in the O&M phase after construction and commissioning.
- Only the visualisation aspect is considered in the demo model from DT enable technologies.
- No high-level technical simulation or algorithmic analysis is involved in the demo version of RamView360.
- Due to lack of data availability, no SCADA/sensor data are considered or linked with the demo model.

7.3 Proof of concept: COREWIND BIM Model

A proof of concept of the BIM model is developed in RamView360, whose technical requirements are listed in Table 7-1. COREWIND's reference FLOW Morro Bay in the North Pacific Ocean is considered as a generic reference wind farm and WTG no. 11 (WTG-11) is used as a generic reference WTG in this demo.

This generic reference floating offshore wind farm comprises 20 wind turbines installed on generic semi-submersible floating structures with centric tower. In this wind farm, a 15 MW reference wind turbine model (IEA-15-240-RWT, https://github.com/IEAWindTask37/IEA-15-240-RWT) is considered. The total capacity of the wind farm is 300 MW. Each semi-submersible floating substructure consists of 3 columns and is moored with a 3x1 line mooring system. The intended service lifetime is 25 years, and additional years for commissioning and decommissioning are considered.

Disclaimer*: The animations and information provided in this proof of concept are considered as a generic reference example. The model shall not be used as a basis for a specific commercial project, as they will vary from case to case. The information is not intended to serve as an exhaustive list of all relevant parameters for a specific project. The authors do not recommend or promote any technology, software or methodology above one another.*

The demo can be accessed from the following:

Demo web-link:		**https://ramview360.xyz/Corewind/**
Login Credentials	**Username:**	**Corewind_RamView360**
	Password:	**Corewind_2020%RAM$**

Table 7-1. Web-browser version requirement for RamView360

Desktop Browsers	Mobile Browsers
Google Chrome v74+	Google Chrome for Android v74+
Apple Safari (Mac only) v11+	Apple Safari for iPhone and iPad v11+ [1]
Microsoft Edge v12+	Microsoft Edge for tablets v12+ [2]
Mozilla Firefox v66+	
Microsoft Internet Explorer v11+	

In Figure 7-1, the GIS map panel of RamView360 is shown. This integrated map shows the geo-data of the wind farm like location, bathometry contours layer to present the water depth in the ocean (in meter) [68], wind farm layout, onshore substation location, inner array & export cable layout, etc. This GIS map is developed in Leaflet [69] (an open source GIS platform) and integrated with the RamView360.

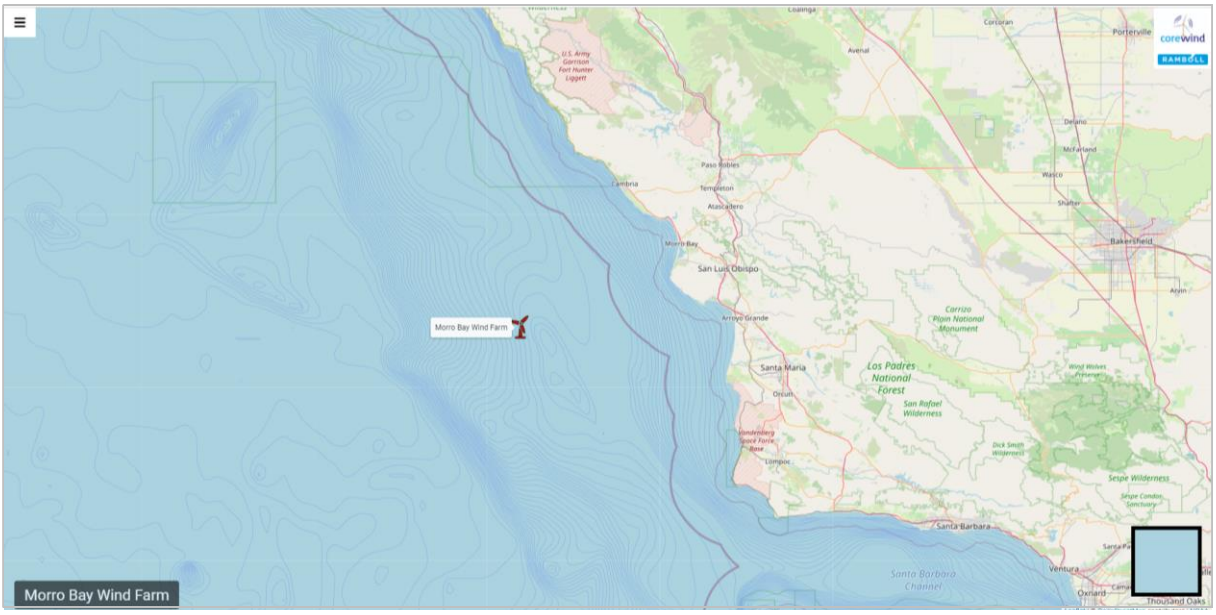

Figure 7-1. RamView360 - GIS map

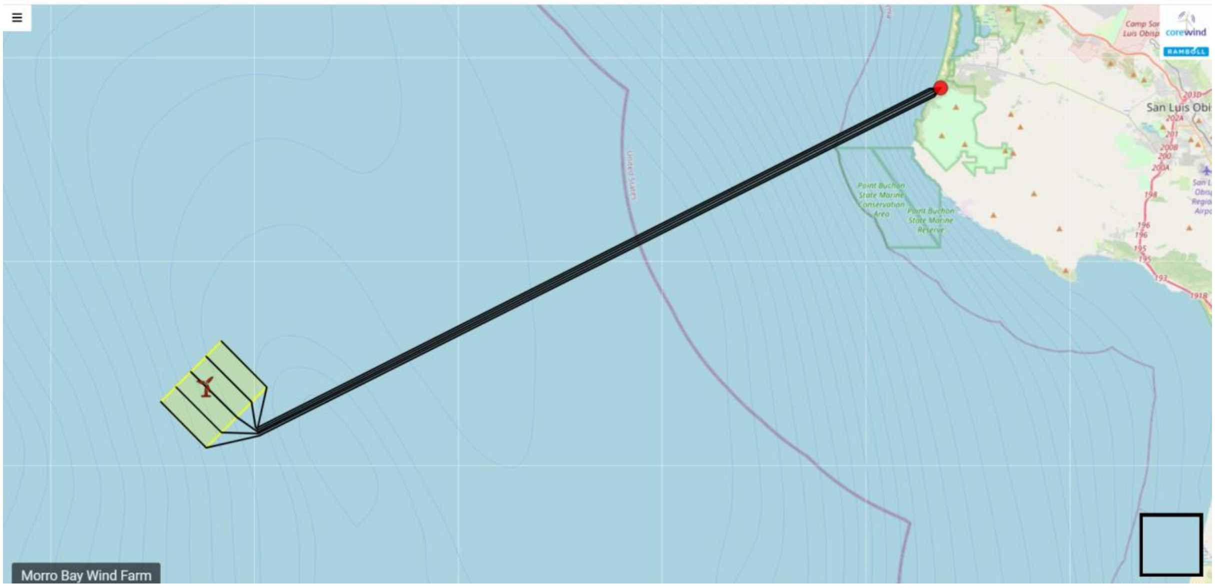

Figure 7-2. RamView360 -Wind farm layout view

As shown in Figure 7-2, the whole WF layout can be viewed in the Leaflet GIS map, which shows details of the cable layout with WTG locations. For this demo WTG-11 (shown in red colour WTG symbol in GIS map) is considered as a reference WTG and developed further with six different examples. The onshore substation Morro Bay is shown in red annotation point as shown in map. By clicking on the WTG-11 user will be redirected to the WTG Dashboard view as shown in Figure 7-3. The user can look around at every viewing location (shown with a red dot) and can teleport to a new location. To help the user easily navigate in the tool, a quick access button panel is given in the tool (shown in the bottom centre part of the screen). A QR code is available for this site, and a quick access button allows the user to share the model starting with the current specific view.

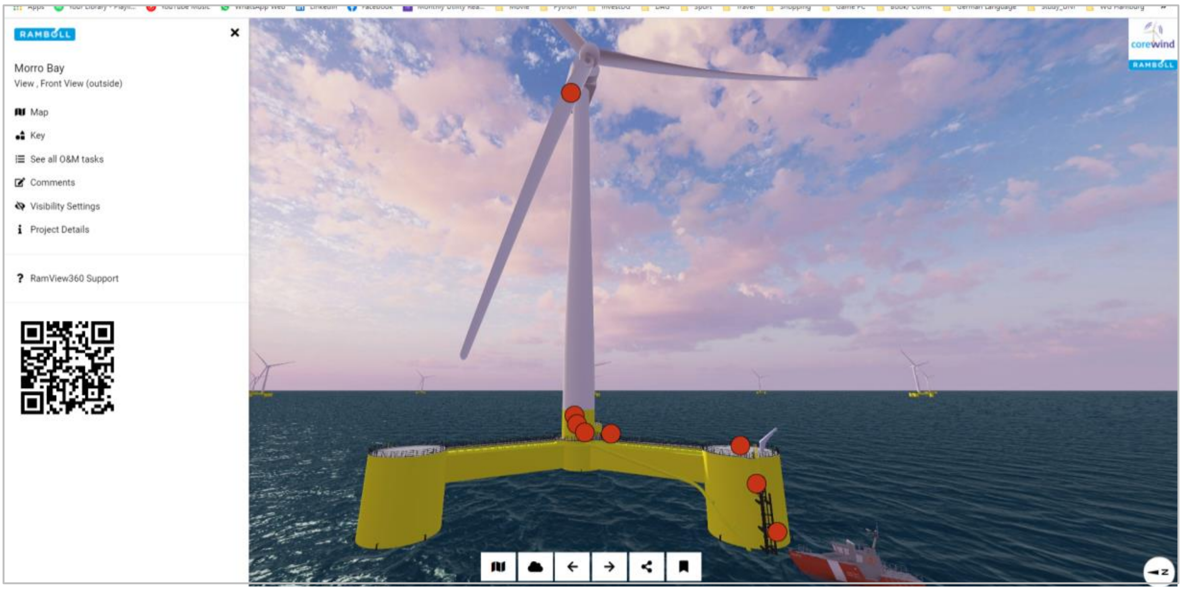

Figure 7-3. RamView360- WTG Dashboard View

This demo contents six different use-case example as mentioned in the following:

- HS&E Training on boat landing ladder,
- Structure inspection of joint between Column/Hull & Horizontal Brace,
- Maintenance example of davit crane components (Davit Crane Motor & Davit Crane Hydraulic Pump),
- Inspection example of J-tube cable connection,
- Inspection example of Mooring Lines,
- Sensor Data Quality example of Acceleration Sensors,

For a better understanding, in this document two examples are described in detail as follows:

1) Davit Crane Electric Motor – Maintenance Example

Figure 7-4 depicts an example of an inspection of a Davit crane electric motor. The user can easily visualize component information by clicking on the annotation point integrated into the RamView360 model, as shown in this figure. An annotation point is a point in a 3D model that is marked to link additional information. With the 3D model, you can view O&M issues, documents, graphs, and so on. Figure 7-4 shows this annotation point highlighted in blue.

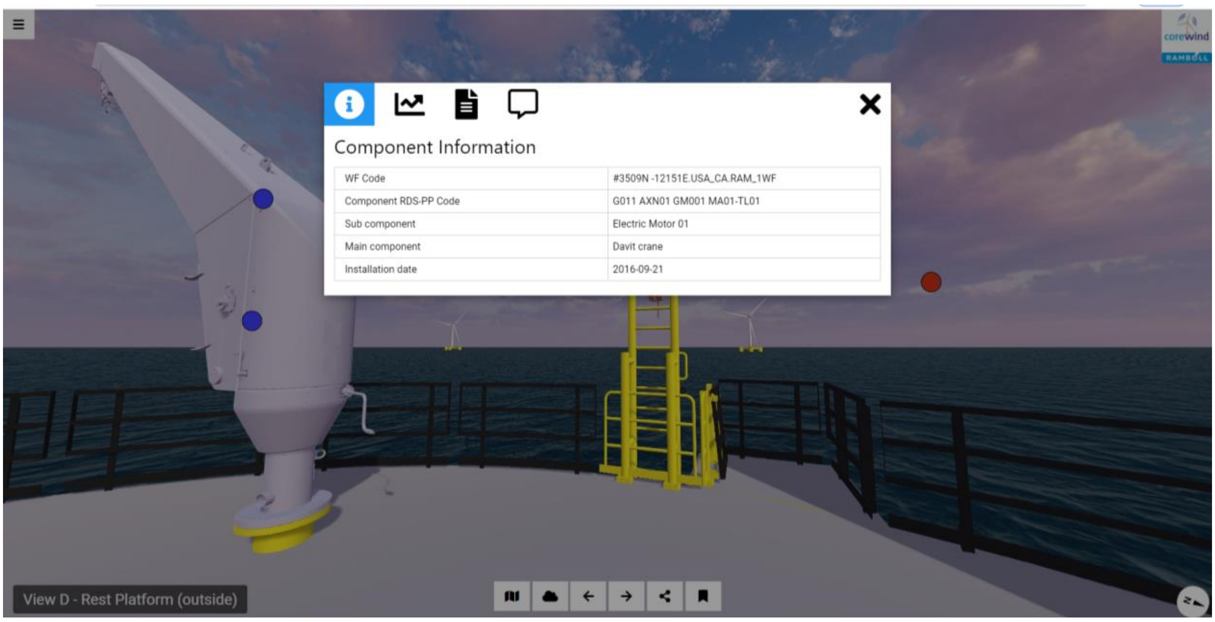

Figure 7-4. RamView360 - Davit Crane Electric Motor Example: Component Information Panel

In Figure 7-5 shown that the key Maintenance data/KPIs can be visualised on overlaid 3D model. This maintenance panel can be linked with internal/external maintenance management system, spreadsheets, etc. which allows the user to visualize the KPIs easily. The user can also approve or reject the performed maintenance task for specific ticket issue shown in Maintenance panel.

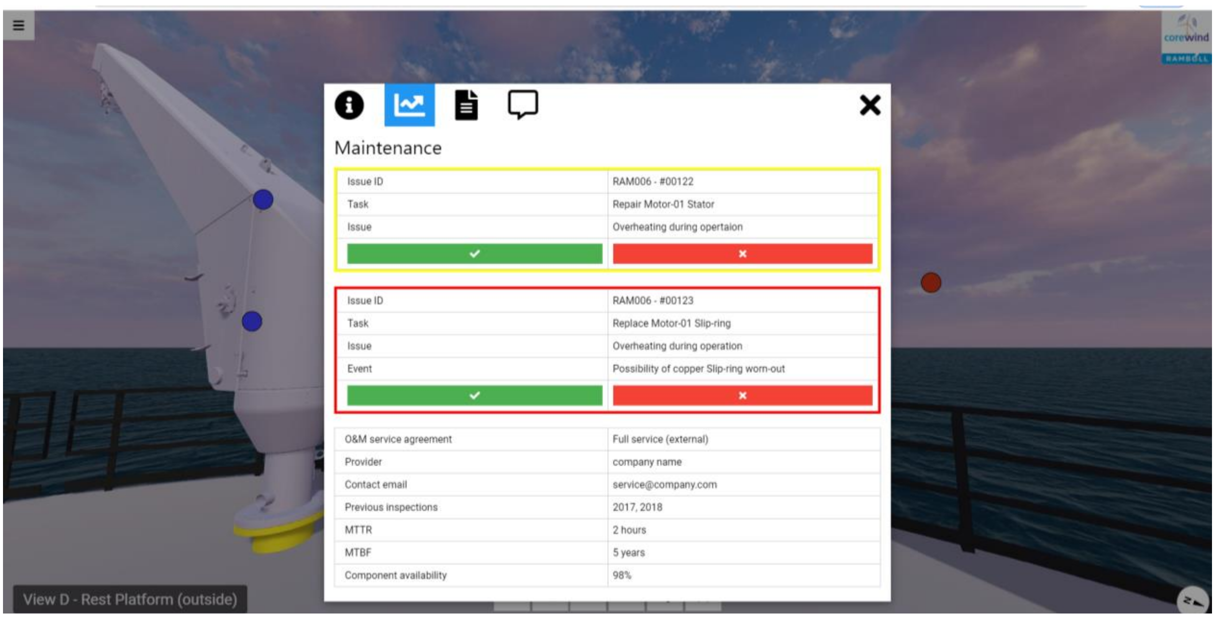

Figure 7-5. RamView360 - Davit Crane Electric Motor Example: Maintenance Panel

In the RamView360 tool, the user can easily link related documents to respective component in 3D model. Figure 4-7 shows an example of different documents linked to the annotation points and on request they can be viewed/downloaded by the user. The example also shows that dynamic files like an Inspection planner Excel file can be linked, as well as static word/PDF files like O&M Manuals, HS&E Handbooks. A feedback panel is used to communicate between different stakeholder of the windfarm.

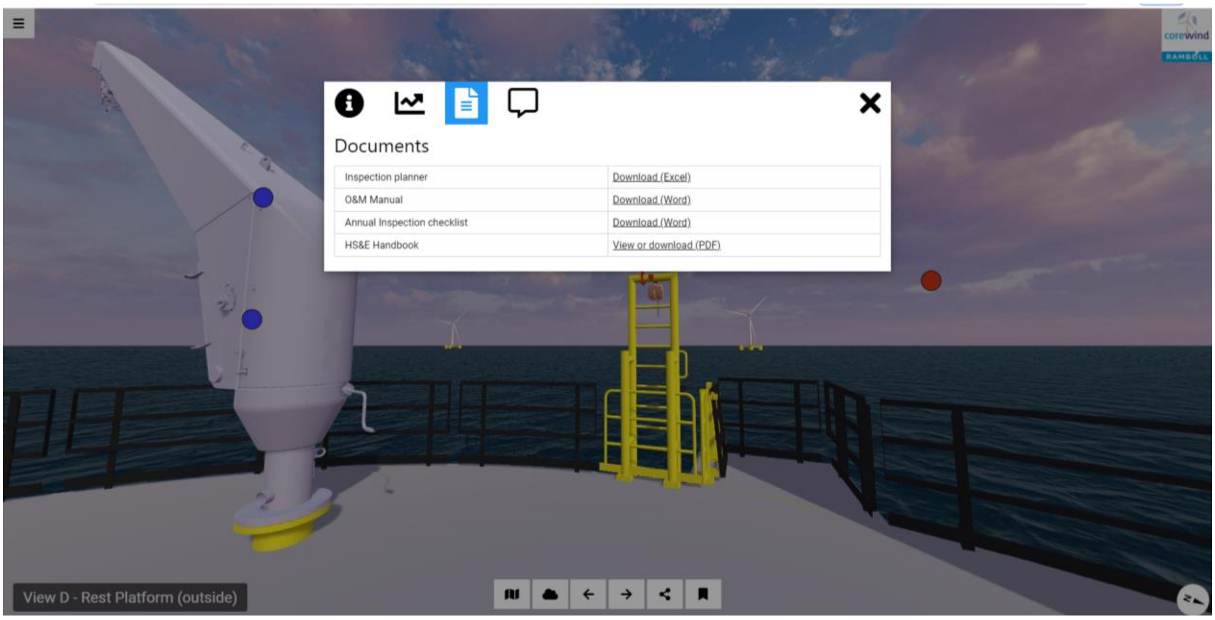

Figure 7-6. RamView360 - Davit Crane Electric Motor Example: Documents Panel

2) Boat Landing – HS&E Training Example

This boat landing example demonstrates how to use RamView360 for pre-planning and training. The component information panel is shown in Figure 7-7, and the documents panel is shown in Figure 7-8. In the document panel, the user can view a video link and/or HS&E step guidelines, which can serve as a guide for pre-training technicians before they arrive on site. The RamView360 model can be visualised in VR/AR devices, which gives a real-scenario view to the user.

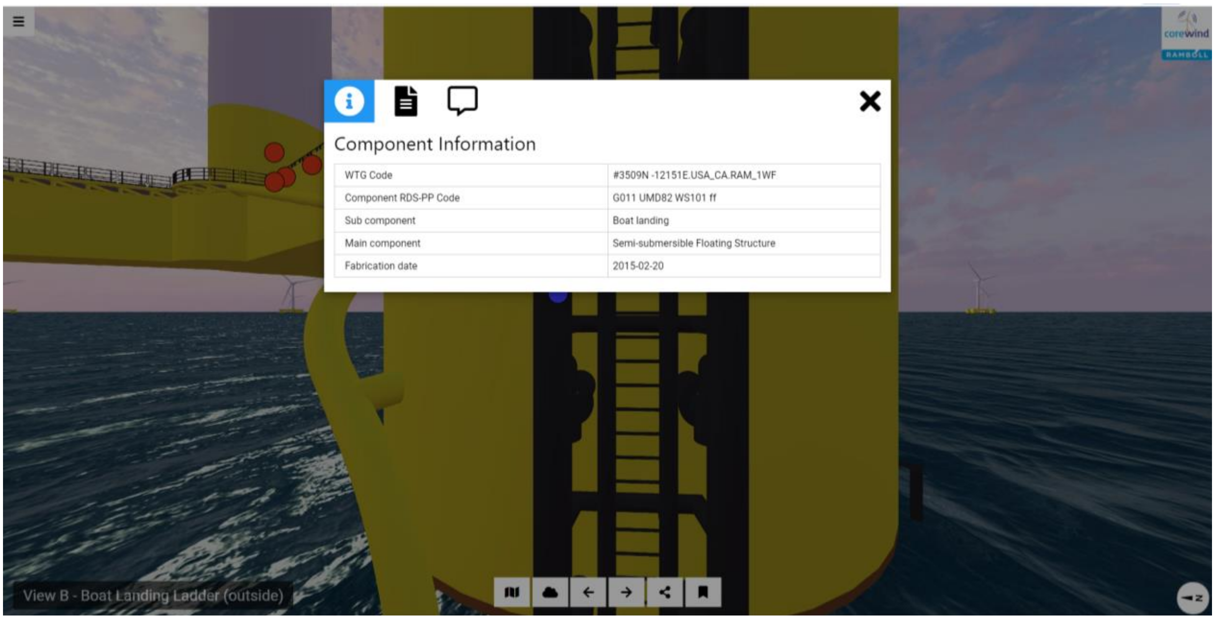

Figure 7-7. RamView360 - Boat Landing Example: Component Information Panel

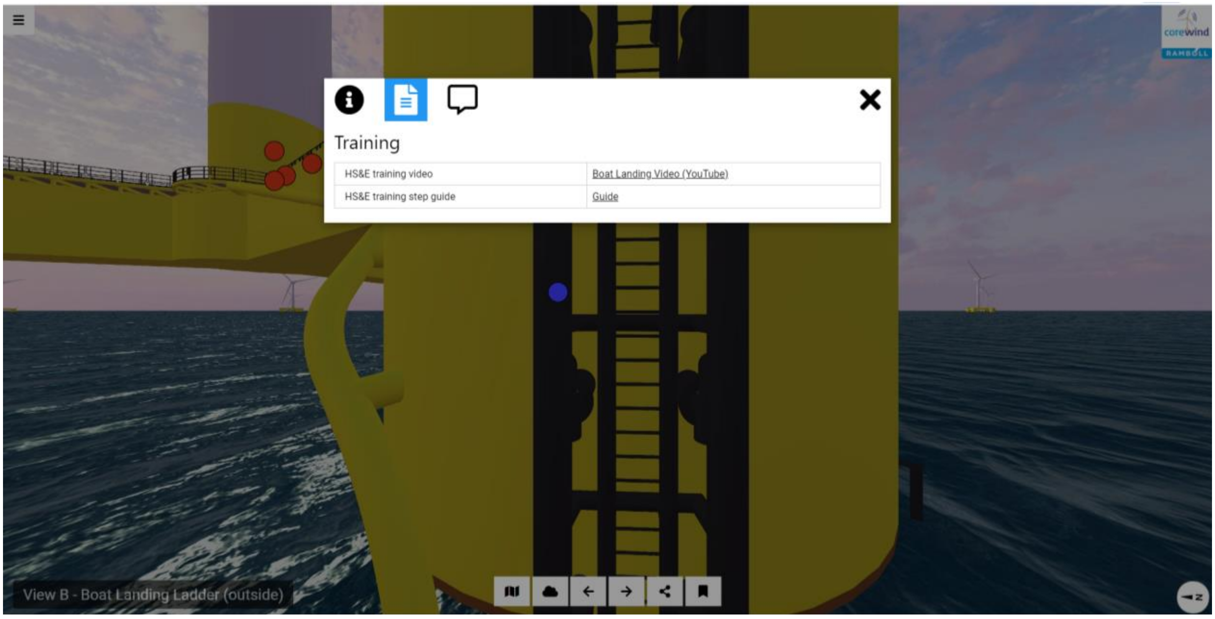

Figure 7-8. RamView360 - Boat Landing Example: HSE Training Panel

RamView360 also has functionality to present the live weather data by linking the RamView360 weather module to any open source/commercial weather platform through APIs. In COREWIND example, an open source weather data near to the Morro Bay area is use from NDBC [59] to demonstrate the functionality and use-case of the tool. The basic weather data like wind speed, wind direction, weave height, weave swell and frequency are mentioned in COREWIND example. From this live weather dataset, real-time plant condition and safety level are estimated to show the working possibility in the site in current weather scenario or not. The weather dataset is updated every 10min according to the data from NDBC.

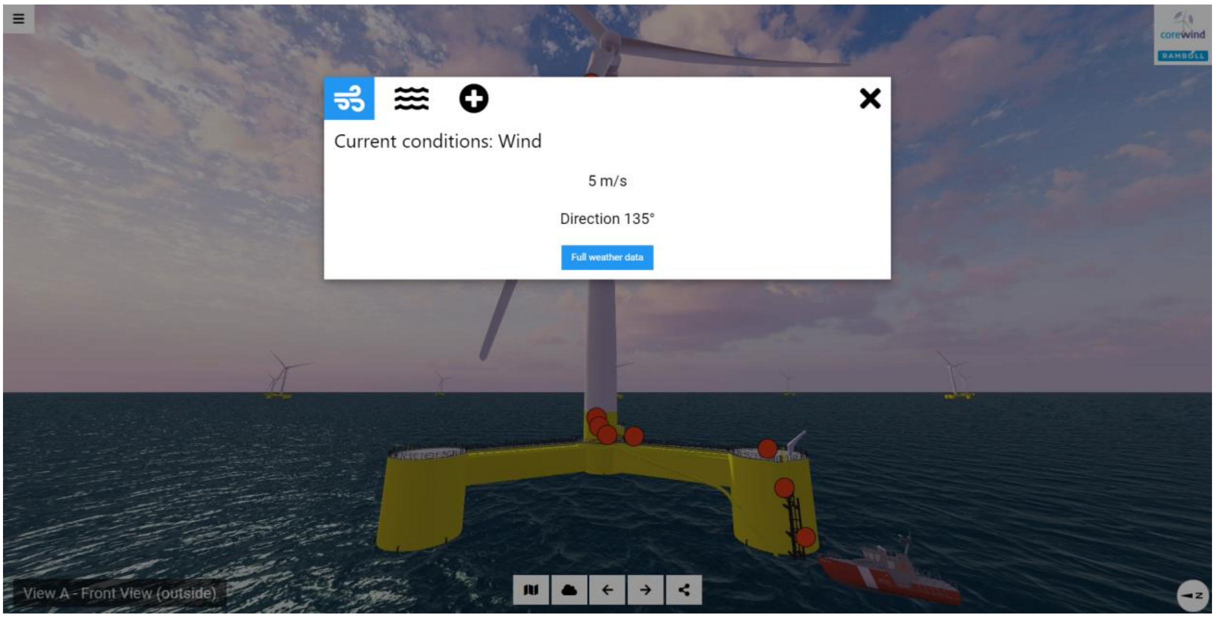

Figure 7-9. RamView360 - Weather Module

7.4 Use Case of BIM Visualisation Tool in the (Floating) Offshore Wind Energy Industry

The RamView360 tool can be used for the whole lifecycle of an asset. The BIM model can be implemented from the development phase until the decommissioning phase of the project. During the development of the OFW project, RamView360 can be utilised to review the drafted design of the foundation models in a 3D environment. While during construction & installation phase it can help to simulate and stimulate the logistic process and material requirements. In the O&M phase RamView360 can be used to visualize sub-component information, O&M tasks, HSE documents, etc. [21]. The BIM concept can also be applied to optimised maintenance activities though an asset information model [22] and help to reduce material required during the fabrication/manufacturing phase by an improved product design [23]. The decommissioning process can be simulated and performed in VSL.

These use cases can be transformed according to the current challenges & requirements of OFW industry. The list of the RamView360 use-cases is mentioned in Figure 7-10 concerning the different stakeholder groups of the OWF project.

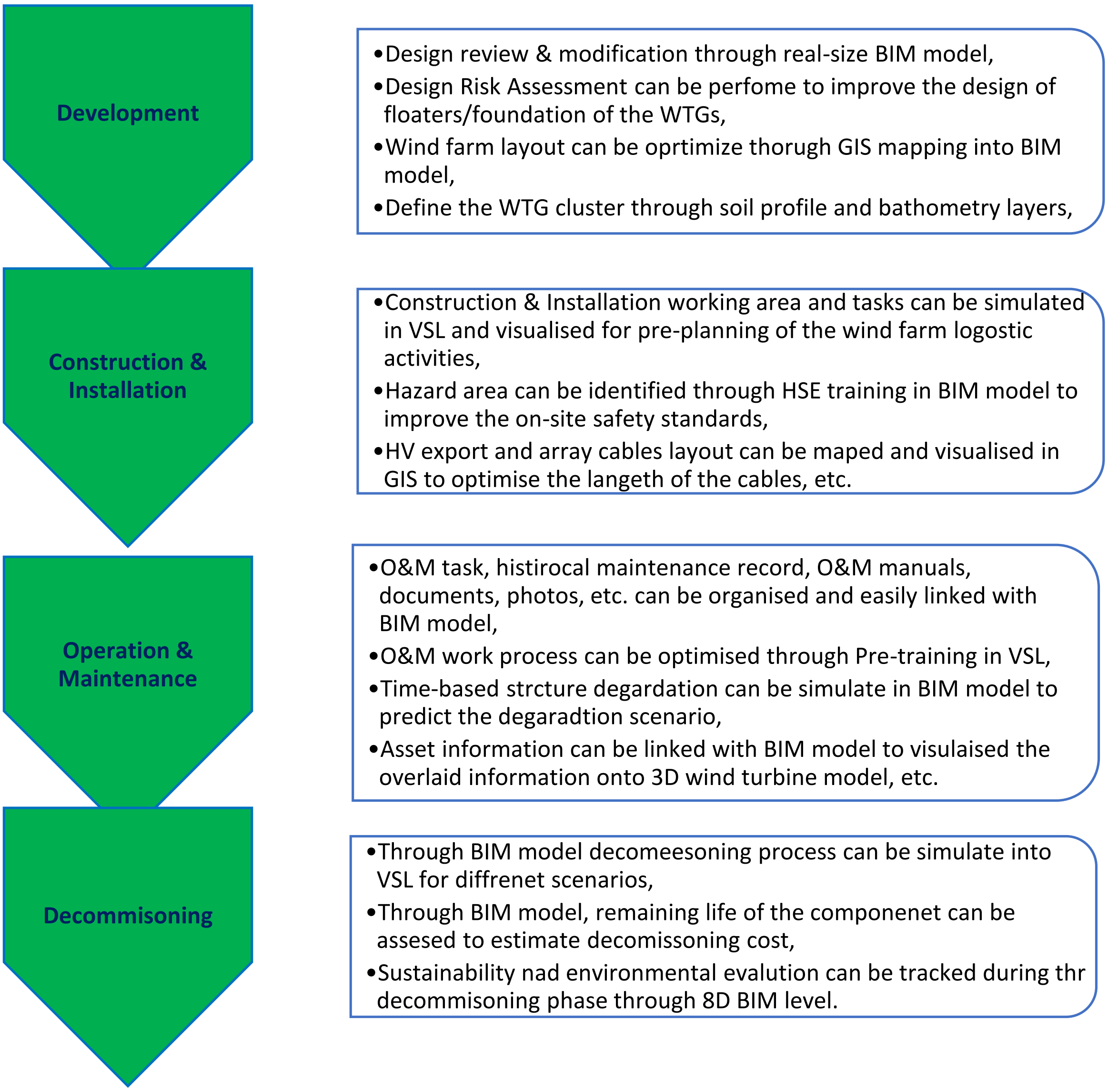

Figure 7-10. Use Case of BIM Visualisation Tool [46]

7.5 Conclusions and future development

The visualisation concepts for the Ramboll Digital Twin technology as well as the BIM visualisation tool RamView360 are discussed. The basic concept of RamView360 is demonstrated, and several use-cases are derived and assigned to key stakeholders. Because the demo version is only limited to O&M activities, it can be expanded to include other phases of the project, such as development, construction, and installation. This RamView360 demo is limited to the WTG level asset information model and can be expanded to a WF level model. Furthermore, the RamView360 tool can be linked with other Digital Twin enabling technologies. This allows the user to see real-time monitoring results in RamView360. An advanced level BIM-model in RamView360 can be used as a pre-training simulator to reduce accidents caused by human error and improve the HSE standard onsite. A detailed model of the floating foundation is used to generate the BIM model in this research work. In addition to the substructure, this BIM modelling approach can be extended to map wind turbine sub-components such as gearboxes, transformers, and so on, as well as substation equipment.

Nonetheless, there is an extensive list of possible future developments, but it is critical to identify potential RamView360 use-cases based on the various stakeholders. The RamView360 tool application can be extended to other areas of the energy business, such as onshore wind farms, HV transmission structures, and so on. Thus, the presented use-cases demonstrate that RamView360 has the potential to be an effective communication solution for floating offshore wind assets using the Digital Twin methodology.

The main outcome of this exercise will be the development of a future concept for effective asset management among various WF stakeholders using advanced visualisation technology such as Ramview360. This improves communication transparency, on-site HSE standards, workflow optimisation, and cost optimisation.

8 Conclusions

This study presents a global overview of the digitalisation options of floating offshore wind farms, their requirements, their advantages and their challenges. Moreover, three complete digital models have been developed in three different areas with different purposes:

- A Digital Twin for real-time visualisation of the wind farm indicators, failure detection and determination of the farm state of health.
- A control model to go beyond maximum power output, increasing the wind farm lifetime as a consequence of a reduced yearly fatigue damage.
- A BIM model that consolidates the information of the wind farm components in a single digital environment with the advantages demonstrated in the construction industry.

The analyses and findings of this report helped to derive the following main conclusions:

- Floating offshore wind farms are complex projects with difficult access to the assets, which leads to the usage of digital models.
- Early failure detection, reduced maintenance duration, reduced unscheduled activities and increased lifespan of the assets are only some of the advantages derived from the usage of digital models.
- The uneven load distribution on the wind farm assets due to the wakes can be solved without practically any impact on the energy yield.

Future works will have the following main objectives:

1. Collect additional information related exclusively to floating offshore wind farms to increase the models reliability and overcome the current lack of data.
2. Increase the functionality of the digital models presented, expanding their usage to installation and decommissioning activities.
3. Improve the accuracy of the models studying additional cases with real data.

To sum up, this report presents alternative ways to reduce costs and the LCOE of the floating offshore wind farms by means of the digitalisation of their assets, as a key procedure leading to a mature technology enabling its usage worldwide.

8.1 Publications from this work

[P1] Alexandra Ciuriuc, José Ignacio Rapha, Raúl Guanche, José Luis Domínguez-García, “Digital tools for floating offshore wind turbines (FOWT): A state of the art” Energy Reports, Vol. 8, pp. 1207-1228 (2022) https://doi.org/10.1016/j.egyr.2021.12.034.

[P2] Héctor Del Pozo González, José Luis Domínguez-García, “Non-centralised hierarchical model predictive control strategy of floating offshore wind farms for fatigue load reduction” Renewable Energy, Vol. 187, pp 248-256,(2022) https://doi.org/10.1016/j.renene.2022.01.046.

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