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Digital twins for offshore wind turbine industry

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ABSTRACT

In recent years, the rapid development of the industry has created a clear need for increasing amounts of energy. As a consequence, the search for green energy sources has become more prevalent in all fields of research. One example that has recently gained significant attention is wind turbines, and due to the lack of space and land, offshore wind turbines. However, this type of energy technology currently presents significant challenges, such as its hostile location and high costs. Therefore, this work proposes the implementation of DTs (DT) as a solution. This paper addresses the state of the art and the concept of DTs, as well as how they could be applied to the offshore wind energy industry. It begins with a definition of the technology and analyzes how the DT works, how it connects the physical reality with the virtual world, and what the key components of this technology are. Then, the current needs of the offshore wind energy industry are analyzed: how DTs are used in design, installation, maintenance, and worker safety, as well as the advantages of sustainability, will be discussed. Subsequently, the current problems that prevent DTs from being sufficiently developed will be addressed: high costs, the need for precise models, standardization, and data policy will be included in this document. Finally, future directions of the industry will be examined, including the classification of DTs at different levels.

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CHAPTER 1: INTRODUCTION

Due to its promising potential to achieve zero-emission goals and its abundant renewable resource, which is wind in the ocean, the offshore industry has grown significantly in recent years. This can be seen in the annual reports provided by the GWEC (Global Wind Energy Council). In Fig. 1, we can observe the annual installations in power capacity by region (Alex, 2023). It is clear that China is leading the way in offshore energy compared to the rest of the world. However, even with China in the lead, Europe and other parts of the world have significant projects in the offshore wind industry. The intentions to advance in this industry are reflected in the Global Offshore Wind Alliance. This alliance, although primarily composed of European members, originated from the Government of Denmark, IRENA (International Renewable Energy Agency), and GWEC (Global Wind Energy Council). The member countries of this association are: Australia, Belgium, Colombia, Denmark, Germany, Ireland, Japan, the Netherlands, Norway, Portugal, Spain, Saint Lucia, the UK, and the USA. These countries aim to achieve 380 GW of offshore energy by 2030 and 2000 GW by 2050.

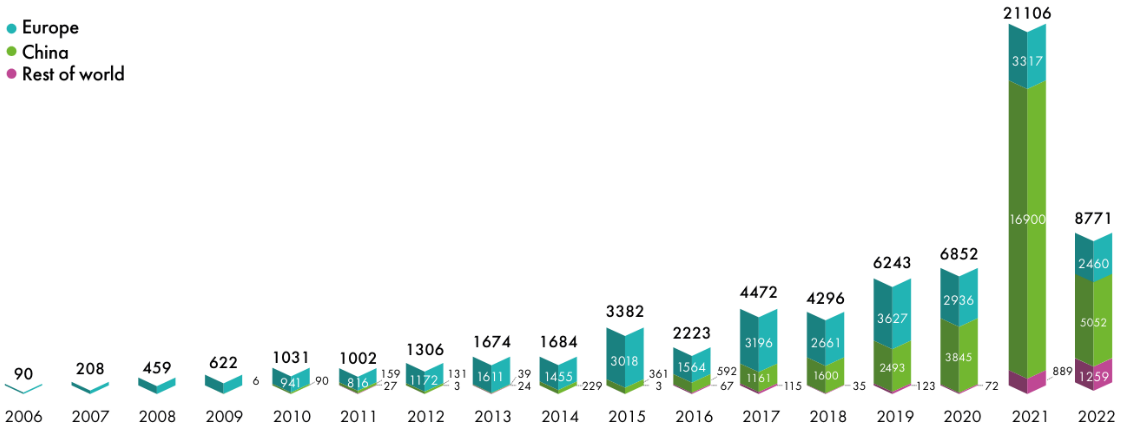

Fig. 1. Global annual new offshore installed capacity per years in MW (Source: https://gwec.net/gwecs-global-offshore-wind-report-2023/)

For these reasons and others, such as the uniformity of the terrain in the ocean, the vast expanses, and the stronger winds, it is evident that offshore farms are a significant investment to consider for focusing our efforts on improving and renewing global energy production. Additionally, these benefits contribute to turbines that are much more powerful and efficient than similar installations on land. However, like all emerging technologies, they present significant problems and challenges, some of which will be reviewed in this paper. As we will see later, one of the most important challenges in the offshore industry involves the operations and maintenance of the farms, due to their remote location from the coast and the oceanic weather conditions. Another issue that requires solutions is the physical integrity and safety of the workers. For these reasons and more, as mentioned in this paper, Digital Twins (DTs) are proposed as a solution. This technology, along with the Internet of Things and artificial intelligence, even in its early development stage, promises great potential to provide solutions and reduce costs, not only in the offshore industry but across all industries, leading to a true technological revolution.

This paper, consisting of four main sections, begins by recounting the history of DTs and providing a definition of them, as well as explaining all their components. In the second section, all the current needs of the offshore industry are listed, compared with onshore, and all the mentioned challenges and more are reviewed, explaining why DTs are a good solution to these challenges. The third section details how DT technology is in its early stages and the reasons why these solutions cannot yet be fully implemented. Finally, the future directions and current levels of DTs are reviewed, along with perspectives from some companies related to the energy sector.

CHAPTER 2: WHAT IS A DIGITAL TWIN?

2.1. INTO THE CONCEPT

With the constant evolution of digital technologies, we have observed significant advancements in the integration of advanced concepts such as the main topic I will discuss in this paper, DT. The DT represents a precise virtual replica of a physical system, process, or product, allowing for real-time simulation, monitoring, and analysis of its real-world counterpart. These advanced technologies enable remote supervision, real-time data collection, and control of cyber-physical devices and systems through robust network infrastructures. This integration and synchronization between the physical and virtual worlds provide organizations with a deeper, predictive, and controlled insight into their operations, optimizing efficiency, decision-making, and innovation in the modern industry. As we will see next, the concept that encompasses DT has been around for more than 20 years now, and it continues to evolve currently, expanding into new fields of technology. The evolution of the usage of the term "*Digital Twin*" is reflected in Fig. 2, whereby searching the Scopus database, we can observe the number of papers related to DT published from 2010 to 2023. 2024 data is not included because it is the year of publication of this work.

2.1.1. Background and development of the concept

Once the term is introduced, we can begin to explore the history, origin, and evolution of the concept itself. It is said that the DT origin is in Apollo's program created by NASA. However, in this initial stage, NASA used a physical twin, which remained on Earth as a spacecraft identical to the one that flew at that time Fig. 3. The first definition appeared in a scientific article dated 2010: "A DT is an integrated multi-physics, multi-scale, probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its flying twin. The DT is ultra-realistic and may consider one or more important and interdependent vehicle systems, including propulsion/energy storage, avionics, life support, vehicle structure, thermal management/TPS, etc. In addition to the backbone of high-fidelity physical models, the DT integrates sensor data from the vehicle's on-board Integrated Vehicle Health Management (IVHM) system, maintenance history, and all available historical/fleet data obtained using data mining and text mining", (Shafto et al., 2010). Although in this definition the term DT is used to refer to the DT of a vehicle, there are terms that are identical for any device and that will be of great importance in this article, such as sensor data, high-fidelity physical models, maintenance history, and data mining.

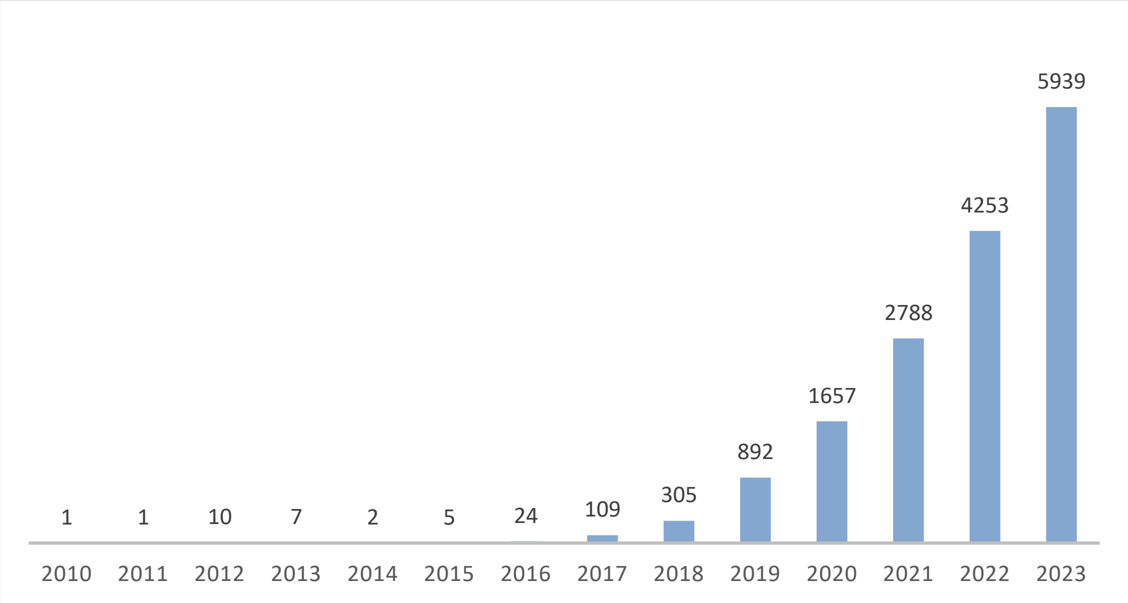

Fig.2. Number of publications with keywords {Digital Twin}. *Source: Scopus*

Despite this being the first definition of the term DT as such, if we go even further back in the concept's bibliography, we find the origin of the idea in a conceptual model used in a Product Lifecycle Management course at the University of Michigan in the early 2003s, where Professor Michael Grieves described what he called the "*Mirrored Spaces Model*" with all the elements that we now know as DT: real space, virtual space and data flow between real space and virtual space. Additionally, this idea also contained the four phases of creation, production, operation/maintenance, and data availability. (Grieves & Vickers, 2017)

If we go deep into the literature written about DTs in the years after 2010, we realize that the vast majority of articles use the term DT to refer to specific vehicles or applications, and not as a general concept. In 2013 (J. Lee et al., 2013), we saw the first time that someone thought of DTs for an application beyond aircraft or spacecraft, using it to duplicate a production line. It was not until 2015 (Ríos et al., 2015) that we found an article that talks about DTs as a product, thus opening the term to be used in more general fields, although this article talked specifically about airplanes.

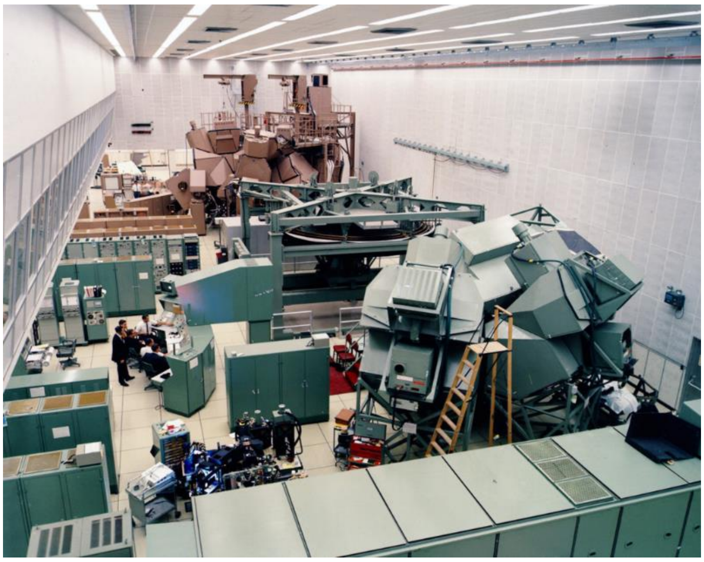

Fig. 3. Apollo 13 Physical Twin at Mission Control in Houston. Image credit: NASA

2.1.2. General definition

Over the years and with the continuous advancement and understanding of DT, there has been a big proliferation in the quantity of definitions used to describe them. As a result of this expansion, the number of discussions and debates about what is and what is not a DT has grown proportionally to knowledge, prompting stakeholders to grapple with the complexities of what exactly constitutes a DT. In (VanDerHorn & Mahadevan, 2021), dedicated to exploring the literature on the subject and attempting to seek a general definition, we encounter up to 46 different definitions of the concept, often differentiated from each other solely by the application of the DT itself. As the authors of this article argue, it is necessary to establish a general definition for the concept before proceeding with any work to avoid confusion. Therefore, this paper proposes one of the most modern definitions, stated in 2018 (Talkhestani et al., 2018): "DT is a virtual model of a physical asset capable of fully mirroring its characteristics and functionalities during its entire lifecycle. It is an approach to manage all generated digital data of a component or system along its lifecycle and retrieve them as needed by simulation or optimization functions to address any occurring challenges". The proposed definition, while limited to only the most basic elements of the DT, thereby avoids delving into specifics with field-specific terminology. By emphasizing simplicity and accessibility, the definition aims to provide a solid foundation for understanding the essence of the DT concept while leaving room for customization and adaptation to specific contexts.

2.2. COMPONENTS OF A DT

Once we have an established definition, we can subsequently delineate the components of a DT: a physical asset, a virtual reality, and the interconnections between physical reality and virtual reality. This is reflected in Fig. 4.

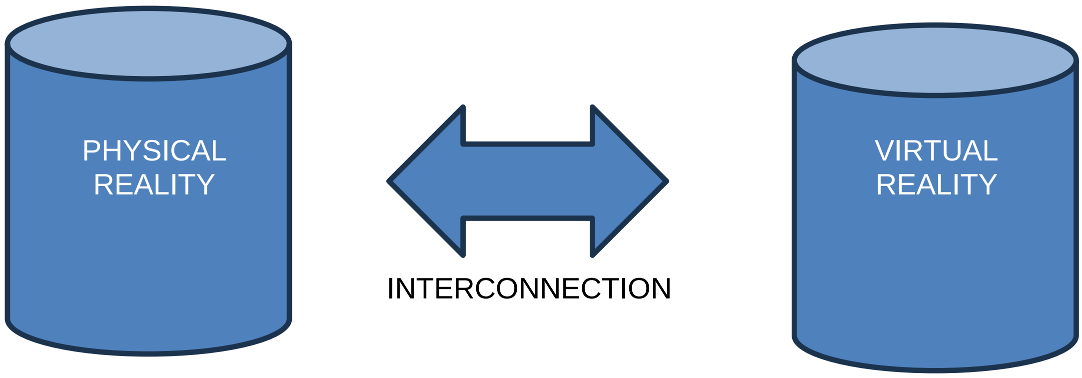

Fig. 4. Schematic representation of DT components

2.2.1. Physical reality

First of all, we find the product or object we wish to replicate with a DT, that is, the physical world. According to (Zheng et al., 2019), the physical space is a complex, diverse, and dynamic environment that comprises people, machines, materials, rules, and environmental conditions. This layer of the DT includes all the objects necessary for product development as well as for its operation, such as data sources, computing resources, and software. All these objects occupy physical space in the real world and are separated and placed in different locations, but they need to be connected by some cloud or Internet of Things (IoT) technology. Once connected, all the data can be collected and processed for subsequent virtualization and optimization.

One of the most important sections of a DT system is the sensors, as this section will be responsible for collecting data that will be processed. In (Juarez et al., 2021), the authors define sensors as components that are directly linked to the devices and serve as conduits for acquiring data and information; once the sensor collects the data, it transmits them to the physical realm for processing.

Some examples of sensors used in the field of offshore wind turbines are listed in (*Wind Turbines: Tiny Sensors Play Big Role | Mouser*, s. f.):

a) **Accelerometers**: Accelerometers, which measure changes in velocity, are used in both onshore and offshore wind turbines to detect and monitor vibrations in various components of the turbine, such as the blades, shafts, or tower. This data can be valuable for predicting fatigue failures or for braking if necessary.

b) **Wind sensors**: Wind sensors are placed atop the nacelle and can be either mechanical or ultrasonic. Because the latter do not require any recalibration unlike the mechanical ones, they are more commonly used in offshore turbines, as they provides an advantage by reducing on-site maintenance due to the difficult access they have. These sensors measure the distance to any object using sound waves, sending out a low-frequency wave and detecting the wave once reflected by the target. By measuring the time it takes for the wave to travel to and from, it is possible to calculate the distance between the sensor and the object.

c) **Temperature sensors**: Temperature sensors are located in positions where an increase in temperature could indicate overheating of a component, whether it be a shaft or any object part of a subsystem subject to high friction.

d) **Displacement sensors**: In wind turbines, monitoring the physical integrity of the system is essential due to the top-loading caused by the tall towers and the size of the rotor and nacelle. Here are three examples of displacement sensors:

   i. *Laser sensors*: Laser sensors can be used to perform this function because they are capable of detecting very small movements in the foundation relative to the tower, caused by jostling due to waves or wind. They work by transmitting a beam of light to an optical receiver at a specified distance. Any relative deviation between the two is transformed into distance measurements, allowing the displacement to be quantified.
   ii. *Capacitive sensors*: This type of sensor determines the distance between the stator and the rotor in the turbine. Their operation is based on the principle of electrical capacitance, which exists between two conductive surfaces that are close to each other and changes depending on the distance between them.
   iii. *Draw-wire sensors*: These sensors integrate a spring-loaded coiled wire with a spool-type transducer. As the wire extends or contracts from the spool, the rotation of the spool is gauged and translated into a measure of alteration. An image of this type of sensor is shown in Fig. 5.

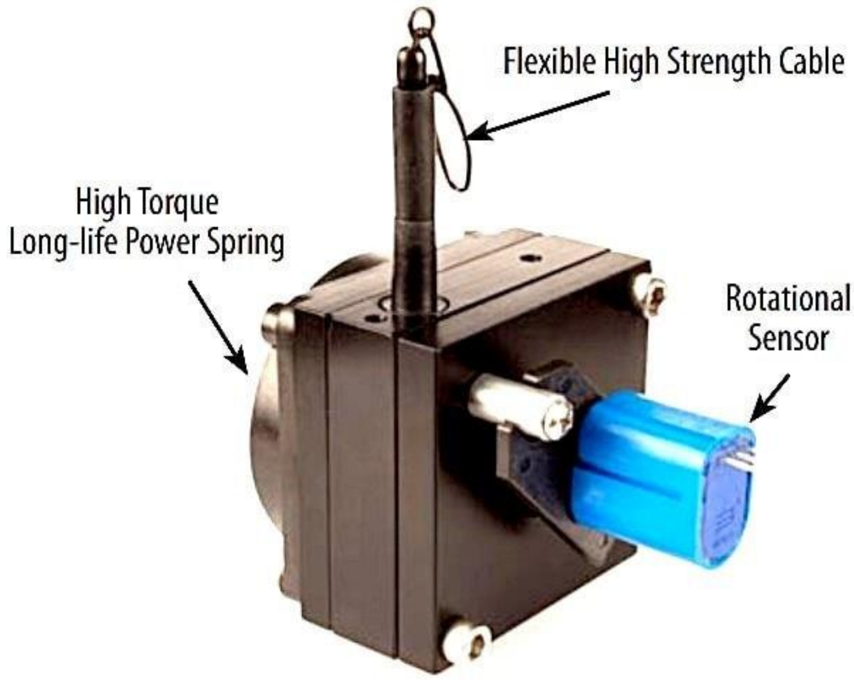

Fig. 5. Draw-wire displacement sensor (Source: Bourns)

e) **Eddy current sensors**: This type of sensor is based on measuring Foucault currents so that the movement of a piece, such as a shaft, can be detected from the electric current generated when it enters a magnetic field.

In some of the literature on DT (VanDerHorn & Mahadevan, 2021), the physical world is often divided into three parts, as shown in Fig. 6: the product itself, the environment that contains it, and finally, the processes that are given between product and environment. In this sub-section we will go a little deeper into them:

a) **Physical product**: The first aspect of the framework is the physical product, which refers to the actual tangible object. It focuses on characteristics like its geometrical attributes, material properties, and functionality. This object, as a physical entity, has boundaries and borders that separate it from other physical entities that, although coexist in the same environment, are not of interest for the creation of the DT. In the case of creating a DT for an offshore turbine, the physical reality would encompass the actual turbine structure; this includes the turbine blades, gearbox, generator, support structure, etc.

b) **Physical environment**: As the second subsection of the physical reality, this encompasses on one hand, the immediate surroundings of the physical asset (for offshore turbines we can talk about the ocean or other wind turbines near there), and on the other hand, external factors that affect the installation such as oceanic conditions, weather, wave patterns, water depth, marine life presence, etc. These elements play a critical role in determining the structural integrity, operational efficiency, and maintenance needs of the offshore turbine.

c) **Physical processes**: We can define this last part of the physical world as the outcome that arises from the relationships established between the physical product and the physical environment. In the context of an offshore turbine, an example of a physical process could be the rotation of the turbine blades, which is caused by the movement of air around it.

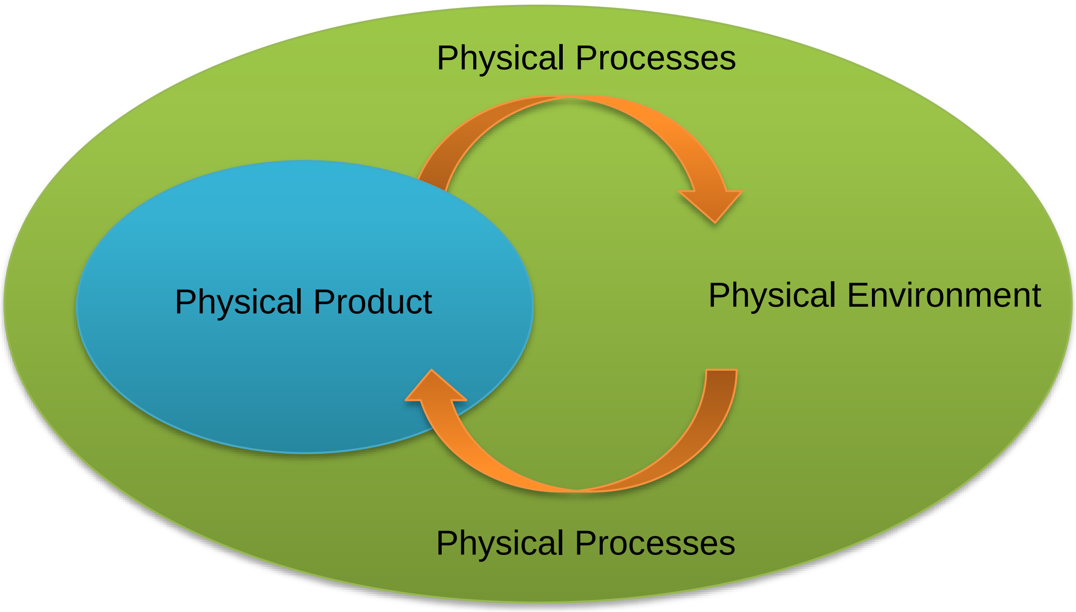

Fig 6. *Graphic that shows the relation between Physical product, Physical environment and Physical processes*

2.2.2. Virtual space

The second component of this division is the virtual space, which, in summary, is the virtual entity representing an idealized form of physical reality. This virtual space is achieved through physical measuring, e.g. using sensors. According to (Zheng et al., 2019), a virtual space consists of two parts:

a) **Virtual environment platform (VMP)**: The function of the VMP is to build a virtual model that integrates an operational environment for the algorithm library. This includes the physical models upon which the algorithms will be based to calculate predictions and actions for the external environment of the DT.

b) **DTs (DT application subsystem)**: This part duplicates the physical space itself, and on this layer, the necessary calculations and operations of the VMP are carried out. This means that there is a direct relationship between the two parts.

2.2.3. Interconnections

Finally, we have the interconnections established between the physical product and the virtual space. This part is defined as a channel through which information flows bidirectionally, meaning from the physical space to the virtual and vice versa. We could say that this interconnection is divided into two phases; the Metrology phase, where a physical state is collected in some type of data, and the Realisation phase, where this data is introduced into the DT. A good example of these two phases is seen in (Jones et al., 2020): "A change in temperature of a physical motor is measured using an Internet-of-Things thermometer (metrology phase), the temperature measurement is transferred to the virtual environment via a web service, a virtual process determines the difference in temperatures between the physical motor and the virtual motor, and then updates the virtual motor such that both measures are the same". We can see this reflected in Fig. 7. This part can be further divided into three layers:

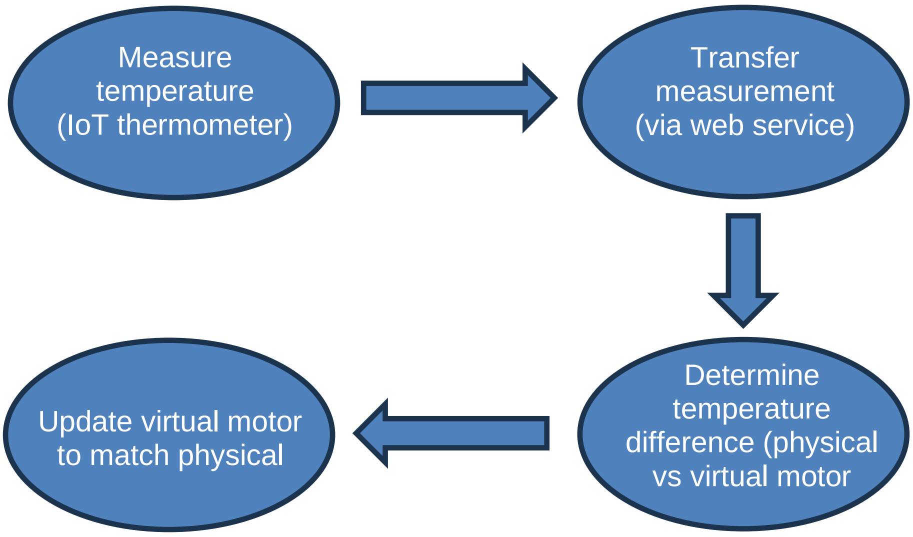

Fig 7. Diagram with sequences of physical-to-virtual phases

a) **Data storage**: Firstly, through a direct measurement of physical reality, the necessary data for subsequent processing must be collected. This includes manual and offline collection as well, for example, visual inspections. Additionally, at this step, data provided by the virtual entity is also collected. All of this is stored in a database.

b) **Data processing**: In (Zheng et al., 2019), the authors divide this step into four sub-steps: data acquisition, data preprocessing, data analysis and mining, and data fusion.

c) **Data mapping**: Data mapping can be defined as the arrangement of physical data that is to be linked in a virtual workspace using modules that facilitate data storage and retrieval processes. There are three main parts of data mapping: time series analysis, correlation analysis, and synchronization.

CHAPTER 3: NEEDS OF THE OFFSHORE WIND ENERGY INDUSTRY

3.1. OVERVIEW

It has been shown that offshore wind energy is of significant importance to the world's renewable energy phase, and thus offshore wind farms play a major role in the supply of electricity. These gigantic wind turbine arrays, located at sea, are subjected to special difficulties in keeping them up and running. DTs represent the virtual clones of offshore wind farms, which are the central tools in addressing such challenges. Through real-time monitoring, predictive analytics, and optimization capabilities, DTs optimize system performance, therefore contributing to the success of the offshore wind power generation industry towards clean and reliable energy sources. Before delving into the main part of this chapter, I will provide a brief introduction to understand the type of structures we aim to work with alongside DT: offshore wind farms.

3.1.1. Introduction to offshore wind farms

Since the inception of the first offshore wind farm prototype in Denmark back in 1991, and especially with the commencement of commercial wind farm assembly along the North Sea coast in the early 2000s, there has been a remarkable surge in proposed projects in this sector across the globe. These ventures span numerous regions, including the United States, China, Japan, Germany, Spain, Belgium, Norway, France, and beyond. Although the first offshore wind turbine was constructed 350 meters from the shore, advancements in technology and research in this field have led to engineering marvels such as Dogger Bank (England) (Fig. 8), which will be the world's largest offshore wind farm once it is finished. Located over 130 km off the northeast coast of England, it is capable of providing energy to over 6 million homes annually.

The main argument for utilizing offshore wind farms, apart from expanding energy generation in countries with limited land territory, is the higher wind intensity experienced in open seas. This is due to the significantly lower surface roughness and turbulence compared to land, resulting in higher wind speeds at lower altitudes than onshore. This translates to a significant reduction in tower height, as well as much lower fatigue and an increase in the installation's lifespan.

As mentioned earlier, the environmental conditions for offshore farms differ significantly from those installed on land, and therefore they require unique construction features. In addition to these conditions, new variables must be taken into account to determine the optimal tower height, such as the maximum sea depth at the farm's location, wave conditions, seabed type, etc.

Fig. 8. Artist's impression of the new 'Voltaire' turbine installation vessel (Source: https://doggerbank.com/construction/)

3.1.2. Offshore vs Onshore

In this section, a brief list of some of the differences between offshore and onshore wind farms will be provided (Colmenar-Santos et al., 2016) and (Esteban et al., 2011), as well as the advantages and disadvantages of this kind of energy generation.

Advantages:

a) Firstly, we find the advantage of the increased wind resource quality in the sea. As we've already mentioned, wind speed is higher most of the time, increasing further away from the coastline. Additionally, since offshore farm towers are much shorter, turbine fatigue is significantly reduced.

b) Another significant and obvious advantage is the vast amount of available space in the sea, leading to larger installations and farms themselves. Furthermore, locating at long distances from the coast eliminates both acoustic and visual impacts from the shoreline. All these factors make it possible to install much larger turbines capable of generating significantly more energy per unit.

c) There is the possibility of utilizing existing infrastructure from other marine energy production facilities. For example, helipads from offshore oil platforms can be repurposed for transporting materials and personnel.

d) The construction, as well as the maintenance and operation of these complex installations, generate a large number of new job opportunities.

Disadvantages:

a) Arguably the main and largest disadvantage of offshore farms is the cost of the processes required for installation, such as construction and maintenance.

b) According to data from (Ioannou et al., 2018), operation and maintenance costs for offshore farms can account for up to 30% of the total investment over their entire lifespan, which is double the proportion compared to onshore farms.

c) Another disadvantage is the complex engineering required to design and maintain the foundations of the towers, which are subjected to adverse conditions at sea. This complexity is compounded by the difficulty of reaching these foundations for maintenance. This typically necessitates additional structures for docking ships or landing aircraft. (Fig. 9)

d) A third disadvantage is the ease of propagation of turbulence caused by the rotation of turbine blades. This is because the roughness of the sea surface is much lower. Thus, greater separations between towers and more complex designs are needed to prevent interactions between turbines.

Fig 9. A helicopter transferring maintenance personnel to an offshore tower (Source: Tesicnor)

3.2. CHALLENGES IN OFFSHORE WIND INDUSTRY

As offshore wind farms carve out an increasingly significant presence in the renewable energy market, unique challenges arise within their marine environment. The aim of this chapter is to delve into some of these challenges, ranging from technical and logistical aspects to environmental concerns. From deep waters to mitigating environmental effects, offshore wind farms face a plethora of challenges requiring innovative solutions and novel strategies.

3.2.1. Offshore farms assessment

While monitoring in onshore farms is entirely controlled, in offshore farms, direct measurements are much more challenging and costly due to their remote location. Currently, monitoring of these farms relies on shore-based reviews using in-situ data collected by monitoring ships, but these data collections are periodic, with a significant time gap between them. Another challenge faced by offshore farm assessment is the economic challenge. As mentioned earlier, the investment required is significantly larger than for an onshore turbine, and this difference is even more pronounced in the realm of maintenance and operation. Therefore, it is crucial to find a way to reduce costs in this aspect.

According to (Li & Wang, 2011), each wind turbine will require up to maintenance visits per year. This means that companies must strategically plan these visits to optimize the intervals between them, as well as take advantage of favorable weather windows.

In addition to complexity and economics, it is also crucial to consider the safety of workers responsible for these tasks. In the offshore wind sector, there have been no reported fatalities, unlike in the oil and gas industry, where there were 5 accidents related to air and water transportation just between 1998 and 1999 (Atkinson, 2010), along with 111 falls, 20 machinery-related incidents, and 2 diving-related incidents. Workers in this sector are exposed to a hostile environment (Fig. 10) and often operate heavy machinery, leading to significant expenses for companies in terms of enhancing safety measures to prevent accidents. Apart from the human cost, accidents result in considerable delays and financial losses. In next sub-section we will delve into some of this risks.

3.2.2. Impact of weather conditions

The challenging location of these farms exposes them to harsh weather and environmental conditions, such as heavy waves, storms, high-speed winds, etc. As mentioned earlier, the weather also influences the periodical revisions due to its difficulty to realize a maintenance operation while there are bad weather conditions. The stochastic and intermittent nature of the wind poses a significant challenge to the construction and maintenance of these farms, necessitating new methods of prediction and remote monitoring, such as LIDAR and SODAR (V. N. Dinh & McKeogh, 2019). These instruments, based on the Doppler effect, use light and sound respectively to determine wind speed.

Fig. 10. A worker inside the turbine’s tower (Source: (Atkinson, 2010))

3.2.3. Risks for health

In the previous sections, the significant impact of the environment and the location of farms on the safety and health of all personnel involved in the offshore industry has been discussed. In this section, a brief report will be provided on incidents that have occurred in this field and the most notable risks in this industry. Before delving into the list of risks, it is important to understand the numbers to quantify how dangerous this industry is. In Table 1, we can see that despite all the harsh conditions and the high number of incidents per year, the number of fatalities is zero. This table only shows incidents that have taken place offshore, as the reports included data on onshore cases, which are not relevant to this work (*Health and Safety Statistics*, s. f.).

Year of report	Incidents on vessels	Incidents on turbine regions	Lost work day injury
2013 (Only Europe)	281	178	66
2014 (Only Europe)	256	378	44
2015 (Only Europe)	213	375	41
2016	284	420	43
2017	616	521	49
2018	278	288	39
2019	245	291	62
2020	232	241	43
2021	274	289	50
2022	325	298	46

Table 1. Incidents report from each year from G+ members (Source: (*Health and Safety Statistics*, s. f.))

Once we know the data, let's proceed to name the most common risks in OWF (Karanikas et al., 2021):

a) **Noise**: Some studies mention noise as a risk since low frequencies and infrasound affect sleep and present various psychological effects. However, this risk is considered anecdotal and not a danger to public health.

b) **Electromagnetic fields**: This is one of the most frequently cited threats during the operational phase of the turbines. For the surrounding community, it is a negligible risk since we are constantly exposed to electromagnetic waves in modern society. However, some studies suggest that close exposure of high intensity and duration can lead to long-term consequences, potentially causing cancers (McCallum et al., 2014).

c) **Shadow flicker**: This is a phenomenon unique to this industry, caused each time a moving turbine blade blocks and lets through light. While epileptic effects in some workers could be considered, studies have shown that these effects are noticeable at frequencies starting from 3 Hz, with most turbines having blade rotation frequencies of 0.5 to 1 Hz. Nonetheless, reports of headaches, fatigue, dizziness, and nausea caused by this phenomenon have been documented.

d) **Vibration**: This phenomenon, considered auditory, only affects onshore farms since there are no populations near offshore farms, and there are no cases where exposure to vibration notably affects workers. However, if we focus on vibration as the movement produced, we observe that various tools or machines can cause vibrations in workers' arms or even whole-body vibrations.

e) **Hazardous chemicals and materials**: The majority of substances that typically cause problems include epoxy resins, synthetic chemicals, and fumes released from fiberglass. These can pose a biological risk as they have the potential to cause cancers and irritations of the respiratory tract as well as the eyes.

f) **Physical risks**: The height of the towers poses a significant danger to workers, as a fall can be fatal if proper safety measures are not in place. Additionally, workers must climb the tower, sometimes several times a day, carrying tools and machines. Furthermore, the limited space inside the turbine's nacelle forces workers to operate in uncomfortable and physically straining conditions.

3.2.4. Marine Spatial Planning

So far, the distribution of marine space usage for infrastructure has been focused in a specific manner, meaning only the precise location for that infrastructure is considered, without taking into account a general overview of the entire space as is done on land. The development of an offshore energy industry raises this issue due to the significant space it occupies, necessitating a shift in vision towards the spatial organization and jurisdiction. A lack of common vision and integrated regulation in laws can lead to problems among stakeholders and potential users of this space. As a solution, Marine Spatial Planning (MSP) can be proposed, which is an approach to planning human activities that considers marine space similar to terrestrial space, including policies and new objectives (Sørensen et al., 2009). According to the Intergovernmental Oceanographic Commission (IOC) of UNESCO, MSP is a process of analyzing and allocating parts of a three-dimensional marine space for specific uses to achieve ecological, economic, and social objectives that are typically specified through political processes. In this way, MSP results in a much more comprehensive way of visualizing a marine region.

3.2.5. Difficulties for cost estimation

Due to the novelty of these types of installations, the calculation of necessary investments remains a set of estimations and uncertainties based on computer modeling and approximations. This is because there are not enough real case studies, leading to a lack of papers discussing actual costs, with most proposing equations and models for calculation. It also depends on other factors such as the type of foundation and fixation to the seabed used. In (Maienza et al., 2020), a lifecycle model for floating farms is studied considering CAPEX (Capital Expenditure), OPEX (Operating Expenditure), DECEX (Decommissioning Expenditure), and LCOE (Levelized Cost of Energy). In (Ioannou et al., 2018), parametric expressions for cost calculations based on a series of simulations are introduced. Most literature suggests dividing costs into 5 parts (Díaz & Guedes Soares, 2023):

1. Project development
2. Production and Acquisition
3. Installation and Commissioning
4. Operation and Maintenance
5. Decommission

In Table 2, we can see an example of cost distribution for a floating wind farm. If the fixation type were solid foundations, the decommissioning cost could absorb more than 10% of the total investment instead of just 4%.

Main area	Subarea and sub %
Development & Project Management (3%)	Project management (67%), Consenting & development services (15%), Site investigations (15%), and Environmental surveys (3%).
Turbine (22%)	Blades (18%), Drive train (19%), Power conversion (30%), Towers (13%), Small components (11%), Turbine assembly (4%), and Large fabrications (5%).
Components & Structure (19%)	Foundations (40%), Subsea cables (25%), Electrical systems (17%), Substation structures (11%), and Secondary steelwork (7%).
Installation & Commissioning (12%)	Turbine & foundation installation (41%), Installation equipment & support services (25%), Cable installation (20%), Onshore works (5%), Installation ports & logistics (5%), and Substation installation (4%).
Operation & Maintenance (40%)	Vessels and equipment (47%), Maintenance & inspection services (42%), and O&M ports (11%).
Decommissioning (4%)	Marine operations (93%), Salvage & recycling (1%), Project management (2%), and Ports and logistics (4%).

Table 2. Cost distribution on a floating offshore wind farm (Source: (V. N. Dinh & Mckeogh, 2019))

3.2.6. Modelling components

Offshore wind farms are large infrastructures, composed of a multitude of interconnected pieces. This poses a challenge when it comes to modeling and assessing potential risks and situations because typically each piece is manufactured by different companies, and therefore their tests and potential trials are carried out independently among pieces. However, the reality is that these pieces are part of a larger ensemble, the wind farm, and therefore any phenomenon affecting the farm will cause interactions between the pieces, resulting in outcomes differing from the independently predicted behavior. Therefore, research is needed in the field of computational modeling of pieces as a whole, rather than unitarily. These types of models are called coupled models, and there are studies on how to carry out this computational coupling between pieces, although at the moment these models are very difficult to compute for current technology (V.-N. Dinh et al., 2013).

3.3. SPECIFIC NEEDS ADDRESSED BY DTS

In the previous section, we have explored the inherent challenges in offshore wind turbines, ranging from the impact of the hostile ocean environment to the difficulties encountered in calculating investment costs. Many of these challenges needs technology that brings innovation and new solutions. By replicating the physical system in a virtual environment, DTs offer fresh perspectives in the realms of operation, functionality, and maintenance. Thus, the aim of using this technology is to minimize the levelized cost of energy for offshore wind farms and thereby compete with fossil fuels. In this subsection, we will delve into the specific requirements that DTs fulfill in the context of offshore wind energy, emphasizing their potential to revolutionize the industry.

3.3.1. Maintenance

DTs (DT) are a recent development and they have proven to be very good tools in the operation and maintenance fields where intelligence decisions can be taken and optimised through use of these softwares. The potential of DT applications in operation and maintenance is underscored by (Errandonea et al., 2020) and (S. Khan et al., 2020). The implementation of condition monitoring as well as fault diagnosis through DT has been seen to reduce unnecessary maintenance tasks significantly.In this sub-section I will write about different strategies that can be applied at maintenance in every kind of systems. This division in five different strategies are seen in best part of the literature about DTs (Errandonea et al., 2020), (Xia & Zou, 2023), (Hanly, s. f.):

a) Reactive Maintenance

This first strategy is based on simply not having any strategy. Also known as corrective maintenance or failure maintenance, this strategy involves acting only when necessary, which means waiting for some part of the system to fail and then taking action to fix it. This allows to minimize costs at its minimum, as there are no maintenance operations planned. This strategy is not typically used in systems or assets that a big failure may cause high costs in the business, for example when replacing a piece of the system is more expensive than doing regularly maintenance. For this reason, in offshore wind farms this kind of maintenance is not used.

b) Preventive Maintenance

This strategy, also known as time-base maintenance (Errandonea et al., 2020) or proactive maintenance (Swanson, 2001), is based on monitoring the deterioration of all equipment and applying small repairs to maintain optimal operating conditions. This way, the likelihood of an unexpected failure is reduced. In this type of maintenance, a series of inspections are scheduled so that after predetermined periods of operation, the system is repaired or checked. However, having scheduled inspections without knowing if they are necessary incurs costs that are usually unnecessary, so this strategy is far from optimal.

c) Condition-based Maintenance

Also known as descriptive maintenance or diagnostics-based maintenance, this strategy does not use a predefined scheme of maintenance operations. Instead, the real-time state of the system is evaluated to determine if maintenance is actually necessary, thus saving unnecessary inspections. For the first time in this list, we see the emergence of the Internet of Things or concepts of DT, albeit in a simpler form and without autonomy to apply solutions by itself (Nikolaev et al., 2019). These technologies are used in coordination with sensors installed in the system to determine possible failures, thereby applying solutions before they occur. With increasing research in the field of artificial intelligence, some authors developed algorithms based that could be used for continuous data acquisition and to provide a detailed status of the system (Mabkhot et al., 2018).

d) Predictive Maintenance

This type of strategy is in a premature phase because sufficient technology levels have not been reached to implement it regularly, although it plays a crucial role in the development of Industry 4.0. This strategy is based on analyzing large amounts of system operation data to detect patterns that may indicate potential future failures, as well as providing an estimation of the real-time remaining lifespan of the system. Using DTs, the system is modeled for all known machine states (normal and erroneous), collected by sensors installed in it, and deep learning algorithms are used to evaluate the state of the model to determine if the system is behaving properly (Zenisek et al., 2019).

e) Prescriptive Maintenance

In this last strategy, we find the highest level of sophistication, as it not only predicts what will happen but also recommends what to do next. It utilizes advanced data analysis and algorithms to recommend specific actions to take before a failure occurs in the system. Like predictive analysis, it uses trend and pattern analysis on extensive datasets collected through sensors. In this case, we see parallels with DTs, as per the definition provided earlier in this work, where the ultimate goal was to act autonomously to predict failures and take independent action. To understand the difference between predictive maintenance and prescriptive maintenance a bit more, the former tells you WHEN the machine might fail, while the latter tells you WHICH part and WHY it will fail (Hanly, s. f.). In Fig. 11, we see reflected the information needed for each type of maintenance.

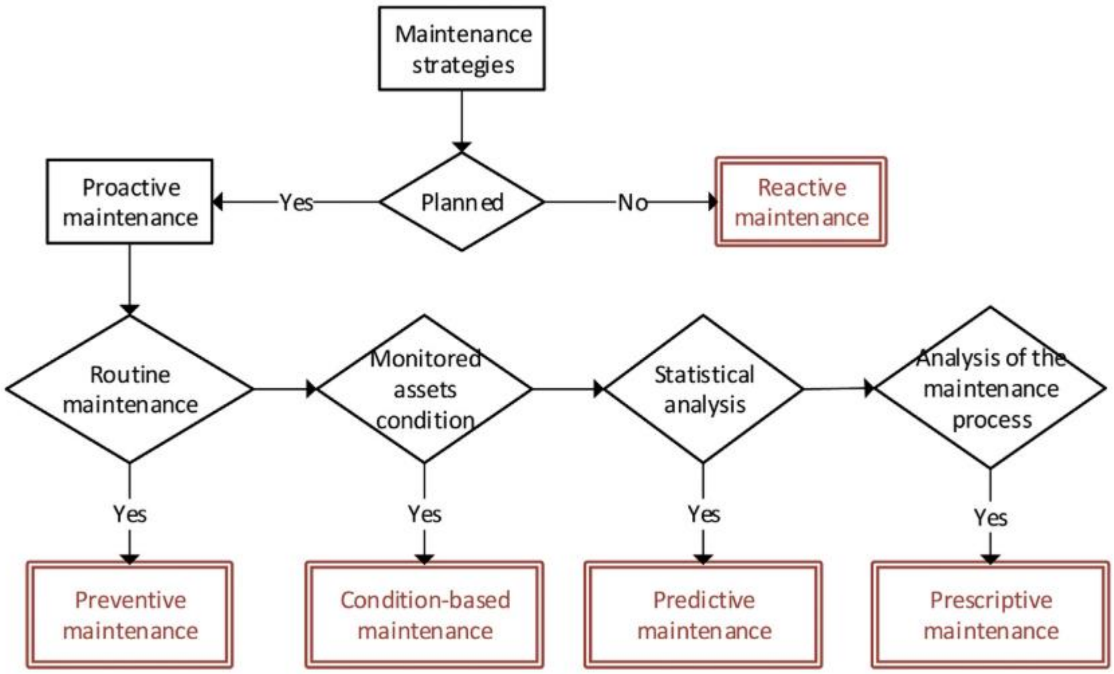

Fig. 11. Maintenance strategies diagram (Source: (Errandonea et al., 2020))

3.3.2. Design and Installation

Historically, during the design phase, simulations with estimated data have been used as input to calculate and size systems. With the growth of technology and the installation of sensors transmitting all kinds of data throughout the entire lifecycle of the systems, it is now possible to adopt DTs as a substitute for these simulations, using real data reused from machines as input. This increases the accuracy of pre-sizing calculations, thus reducing the safety coefficients previously adopted by engineers during the initial phases. The reduction of safety coefficients used results in a decrease in design costs, as unnecessary over-sizing and material waste are eliminated. In this paper (Söderberg et al., 2017) we see an example of how a DT is used for optimization in the design phase of an arbor press.

On the other hand, we have the installation phase, in which various efforts have been made to reduce the complexity and challenges it entails due to the harsh environment. In Table 3 we see some examples of applications of DTs for installation extracted from (Liu et al., 2023):

Application	Original work
A monitoring system for a jacket platform is implemented to limit superstructure movement to a specific level by continuously monitoring and controlling it both before and during the float-over installation process	(Tian et al., 2022)
Accurate measuriement and analysis of multi-body systems' response under complex loading conditions so that the construction can be executed correctly	(Fugro's QuickVision® Technology Supports Installation of Arcadis OST-1 Wind Farm from a Heavy Lift Vessel | Fugro Expertise, s. f.)
Performiance of time-domain simulations on a multi-body system comprising a catamaran, spar, and wind turbine, aiming to analyze the system's motion response under different wind loads and wave conditions	(Z. Jiang et al., 2018)
Integrated matching method based on the installation vessel, numerically simulated with ANSYS-AQWA	(Chen et al., 2020)
Simulation of load transfer during the twin-barge float-over installation and investigation of the dynamic response under impact loads	(W. Tao et al., 2020)

Table 3. Different works that applies DT technology to installation phase

3.3.3. Workers' safety

Another aspect to consider is the safety of the offshore wind farm operator. This new approach to safety management is called proactive, as opposed to the traditional (reactive) method, it continuously and in real-time alerts installation personnel of potential hazards that may occur (Bohn & Teizer, 2010). But for achieving this kind of security management, it is necessary to collect loads of real-time data. Although in this field, DT and the IoT are in a very early stage, numerous experiments and studies have been conducted to demonstrate that this technology can also be used to enhance safety on the farms. One of the experiments conducted in a real installation using the DT as defined in this work is that of (W. Jiang et al., 2020). In this experiment, a safety management system is created by synchronizing risk data between a virtual space and a physical space, including scene reconstruction, data processing modules, and intercommunications. In Table 4 we find some more examples of them.

Application	Original work
Positioning base stations to track personnel and positioning algorithms to collect data	(Soltanmohammadlou et al., 2019)
Stereo camera system within visual range for tracking	(Y.-J. Lee & Park, 2019)
Fusion of different sensors as radio frequency identification (RFID) and GPS	(Ergen et al., 2007)
Wearable insoles to recognize walking and advice from possible falls	(Antwi-Afari et al., 2018)
Camera-based health assessment for working posture	(Zhang et al., 2018)

Table 4. Different works that improves security management using DT or IoT

3.3.4. Sustainability

DTs are not limited solely to enhancing the efficiency and design of OWFs, but they also have significant potential to make advancements in the sustainability and conservation of oceanic ecosystems. By replicating them, DTs enable scientists and engineers to simulate scenarios and assess environmental impacts, as well as design new conservation strategies. However, the majority of research on DTs is focused on the farm system itself, and the environment formed by the fauna, flora, and seabed is often overlooked. Therefore, this is one of the fields with the least investment currently.

As a reference DT in sustainability, we find the DT Ocean (DTO), a project undertaken by the European Commission, announced in 2022. Although this project has great potential, it is also affected by a lack of funding. "The DT Ocean is a consistent, high-resolution, multi-dimensional and near real-time virtual representation of the ocean, combining ocean observations, artificial intelligence, advanced modelling operating on high-performance computers and accessible to all." (*DT Ocean*, s. f.).

In general, DTs can be applied to sustainability in these fields:

a) **Reducing overfishing:** DTs present themselves as an interesting innovation for sustainable fisheries. They create virtual fishery systems that help in monitoring actual fish populations and fishing activities almost as they happen. In these virtual fisheries, autonomous agents can take notes of species abundance, suggest appropriate catch size and time to fisher folks. This could help for have a registration of fish populations near the OWFs.

b) **Modeling and predicting marine pollution:** In coastal pollution and oil plus gas pollution, DTs help a lot. They include various sources of data in monitoring pollution through the use of autonomous agents that detect where the alerts should be sent and come up with oil spill scenarios: timely and nearly real-time. It also enhances coordination among response units towards research on underwater noise pollution, thus supporting efforts for wind farm sustainability — which is identified from the adverse environmental impact due to such coastal areas.

c) **Marine Spatial Planning:** DTs are highly useful for Marine Spatial Planning (MSP) because they enable individuals to test different planning options in a virtual version of the ocean. We can use this to find the best locations to install wind farms and other facilities at sea while simultaneously protecting the animals and plants that live there, reducing noise, and preventing harmful substances from spreading. DTs help make offshore wind farms more sustainable by promoting nature-friendly construction and encouraging multiple uses of the ocean.

CHAPTER 4: MAIN CHALLENGES FACING DT NOWADAYS

Up to now, we've delved into the definition of DTs and the history of the concept, as well as the needs of the offshore wind energy industry and how DTs can address some of those existing challenges. However, as mentioned before, DTs are still a field under development and present significant hurdles and challenges to overcome through research. As Mark Halpern said in a PDT conference: “Transformation is on its Way, But Few Tools are Ready”. This is what the next chapter will address: the roadblocks that must be removed for DTs to be effectively applied. In Table 5 (Rasheed et al., 2020) we find some actual challenges that DT industry must confront and its respective enabling technology, but we only will go deep in some of them.

Challenges	Enabling Technologies
Data management, data privacy and security, data quality	Digital platforms, cryptography abd blockchain technologies, big data technologies
Real-time communication of data and latency	Data compression, communication technologies like 5G and IoT technologies
Physical realism and future projections	Sensor technologies, high fidelity physics-based simulators, data-driven models
Real time modelling	Hybrid analysis and modeling, reduced order modeling, multivariate data-driven models
Continuous model updates	Big data cybernetics, hybrid analysis and modeling, data assimilation, compressed sensing and symbolic regression
Transparency and interpretability	Hybrid analysis and modeling, explainable artificial intelligence
Large scale computation	Computational infrastructure, edge, fog and cloud computing
Interaction with physical asset	Human machine interface, natural language processing, visualization augmented reality and virtual reality

Table 5. Challenges related with its respective enabling technology (Source: (Rasheed et al., 2020))

4.1. HIGH COSTS

Even though the improvement of computational technology continues to drive down costs, this aspect remains one of the major hurdles that DTs present to companies. This is because, ultimately, DTs are nothing but an investment, and their real benefit lies in saving money for the company rather than generating it, as could be the case with any other investment. Because of this, it's very difficult for companies to quantify the ROI and thus decide whether it's profitable or not (Mihai et al., 2022).

In (West & Blackburn, 2017), the authors analyze the economic challenges that the United States Air Force would need to overcome if they wanted to implement DTs in their weapons development system. Their conclusion: “The above analysis suggests the costs of Digital Thread and DT make the concepts impractical to fully implement. [...] DT development and sustainment could cost between $1 and $2 trillion—roughly equal to the combined Air Force/Navy RDT&E budget request for FY17” (West & Blackburn, 2017).

In 2018, at PDT Europe conference, Gartner’s analyst Marc Halpern said that, although there was a high level of knowledge regarding technology and structure, there was a common ignorance about the concepts of money and time when it comes to DTs: “It will take longer and will be more resource-consuming than anyone can imagine to get these solutions in place” (*DTs*, s. f.-b).

In conclusion, the economic considerations surrounding DTs underscore the need for careful evaluation and strategic improvement before implementation.

4.2. FAITHFUL REPRESENTATIONS

Just as DTs have been created to make faithful virtual representations of a real object, this itself brings a great challenge in achieving high fidelity and quality. A DT without these characteristics will not correctly simulate scenarios during testing and will be useless. Knowing that there are two ways to build a DT, the first being a specification-based approach with engineering artifacts and the second using ML (Machine-Learning) methods, experts state that the best approach is a hybrid one combining both. This hybrid approach simultaneously eliminates the real-time data inconsistencies inherent to specification-based methods and provides the potential capability to model the correct behavior of the physical counterparts (Suhail et al., 2022).

4.3. STANDARISATION

Not a few authors in the literature on DTs claim that one of the major problems in the implementation of this technology has its roots in the lack of standardization (Botín-Sanabria et al., 2022), (Harrison et al., 2021), (M. Singh et al., 2021). Being a technology in an early phase, there are many branches of research open at the same time, thriving in parallel, each operating differently due to the lack of a common starting base that an established technology has. Without a set of written regulations and standards to organize and unify all participants in the world of DTs, there can be understanding problems, as if each one were speaking their own language.

According to (S. Singh et al., 2018), what has happened is due to the development of

DTs following a proprietary format, that is, the format of small-scale industries. This model means that each company has its own way of communication, data acquisition, storage, etc.

This fragment from (*SAE to Create Standards for IoT, Big Data and the DT in the Aerospace Industry*, s. f.) perfectly summarizes the current state of standardization: "The status of IoT standardization is effectively an alphabet soup. Everyone has their own system for communicating, getting online and storing data. This might be fine and dandy if you want your IoT device to be exclusive to your partner devices. It may also be fine if you are making a consumer product. But when you start to look at the aerospace, automotive and manufacturing markets, then you need to follow standards".

Using a large-scale project as an example, without the existence of formal standardization, communication and integration between different organizations would be impossible or would hinder cooperation in a way that would compromise the safety and quality of the final result.

For these reasons, it is necessary for the institutions responsible for drafting the standards to focus their efforts on this problem as soon as possible, although some are already working on it. Some of these are, for example, the Society of Automotive Engineers (SAE), which is in the process of standardizing IoT, focusing on issues related to data (ownership, governance, interoperability, management, security) (S. Singh et al., 2018), or ISO 23247 (DT Manufacturing Framework), which is focused on creating a generic development framework that can be used for specific use cases. This standard has proposed four parts: Overview and general principles, reference architecture, digital representation, and information exchange (Shao & Helu, 2020).

4.4. DATA ISSUES

In this section where we will talk about the challenges we have to face related to data, and probably this will be the longest subsection of the challenges mentioned in the paper, since the DTs base their operation on the collection and exchange of data and therefore it is the biggest source of problems.

4.4.1. Cybersecurity

Just as the field of DTs has expanded exponentially in recent years, so have the problems related to cybersecurity. DTs operate based on IoT, primarily relying on IoT sensors installed in the machinery. At this point, vulnerabilities become more noticeable for potential cyberattacks. These vulnerabilities give rise to the discussion that will be addressed in the following section. (MAPP, 2020)

4.4.2. Public or Private Data?

With the aim of preventing security breaches and data theft, most companies choose to store all their data in data silos and make them completely private. However, this leads us to the following problem: the lack of transparency. The creation of data silos to prevent breaches can be detrimental to the value chain, as these imply inconsistency and synchronization problems. This, combined with poor data privacy policies (which is very possible in a relatively immature field like DTs), leads to internal problems within the same company (M. Singh et al., 2021). If we look from the perspective of an external company trying to implement a DT in the company that owns the data, all these aggressive privacy policies are a real obstacle to efficiency (MAPP, 2020). This is a difficult debate to resolve because, while keeping data under lock and key affects the functioning of the DT, not doing so makes the DT much more vulnerable.

4.4.3. Software Obsolescence and Updates

As we have seen, DTs are typically used for applications with long life cycles, such as offshore farms, aircraft, production systems, ships, etc. This brings about a problem: the physical product's life can exceed the designed lifespan of the DT (*Confront Key Challenges To Boost DT Success*, s. f.). This means that the software may become obsolete before the object ceases to be useful. Additionally, due to the nature of these assets, they will almost certainly evolve in some way (for example, a platform expansion), and the DT must do so as well to remain true to reality. As a result, the owner of the physical system may become permanently dependent on the software provider for updates to extend the life of the DT. This presents another challenge to overcome, requiring DT designers to plan for longer life cycles and some form of updating different from typical software.

4.4.4. Data collection

The fact that the asset has to be cloned identically in a virtual world results in an enormous amount of data to collect, store and send, and this poses several problems for the industry to overcome (Suhail et al., 2022):

a) **Find the optimal volume:** This first aspect is about finding a balance: between including too much data, which can lead to information overload, and including too little data, which can result in inaccurate predictions.

b) **Frequency:** Again, it's about finding the balance. For example, recording a series of vibrations at a frequency of once per minute will surely leave errors undetected, but sampling every half second can affect the quality of the transmission (F. Tao & Qi, 2019).

c) **Duration:** This is about selecting which data is truly necessary to store, as storing large amounts of data is very expensive. However, some data must be stored because it helps to uncover behavior patterns and thus model more accurately (Kusiak, 2017).

4.5. REUTILIZATION

How to reuse twins for controlling various physical devices? (L. U. Khan et al., 2022). One way to make DTs more accessible could be their reuse, but we must first ask ourselves if this is possible and, if so, whether it will affect their performance in any way. By their nature, DTs require significant efforts to create exact replicas of the selected object, but with some learning methods, they can be trained to generally learn any type of data. However, as some authors (Emmert-Streib et al., 2020), (Pouyanfar et al., 2018) suggest, these learning methods may result in performance failures.

CHAPTER 5: FUTURE DIRECTIONS

In the previous chapters, the fundamental concepts of DTs were defined, the needs of the offshore industry were discussed, as well as the challenges to be overcome, and finally, the current obstacles to the real implementation of DTs were examined. In this chapter, we turn our attention to the future of DT development, examining its upcoming directions and the open research areas that exist.

DT technology can be divided into several sub-technologies, including IoT, AI, big data, simulation, and cloud computing, among others. It can be said that DTs follow a parallel path to all these technologies, advancing at a similar pace due to the global trend towards increased digitalization. This trend became particularly noticeable during the pandemic period from 2020 to 2022, when digitalization not only became necessary but also evidently facilitated many processes and operations. Therefore, there is a clear latent potential behind DTs, which is highlighted by market estimates. Data from 2021 shows an expected growth rate of 58%, with the market value projected to reach 48.2 billion USD by 2026 (M. Singh et al., 2021).

In a 2018 article by IEEE Future Directions (*DTs*, s. f.-a), some experts argued that it is possible that in the not-too-distant future, a robot-DT symbiosis could exist, where each robot would have its own DT. When the physical asset becomes obsolete, it would be replaced by a new one that learns from the DT of its predecessor. Experts even see the possibility that this DT-learning method could be applied to human workers as well. This would undoubtedly represent a total paradigm shift.

5.1. Classification in levels

First of all, we will address some testimonies obtained in an interview with an essential part of the development of DTs: the industrial partners, that is, the companies that may end up using them. But before that, it is important to consider a classification (Fig. 12) that allows us to understand the different levels of DT according to their technical capabilities. This will be important as the companies mention these levels at various points during the surveys. Although there are numerous classifications of this type in the DT literature, in this work we chose the one adopted by (Stadtmann et al., 2023), (Sundby et al., 2021), (Elfarri et al., 2023):

a) **Level 0 (Standalone)**: This type of DT is not considered a DT in all definitions since it exists without the physical asset. It is typically used for pre-design purposes or to calculate costs and benefits. Specifically, for offshore farms, it could be used for positioning or climatic studies.

b) **Level 1 (Descriptive)**: At this level, data flow between the physical and virtual models comes into play. This DT simply duplicates the physical asset and displays data without drawing conclusions on its own. In other words, all data must be interpreted by a human. It can already generate value as it provides information without the need to collect it on-site.

c) **Level 2 (Diagnostic)**: At this level of capabilities, the data collected by sensors is combined with data analysis tools, allowing the detection of certain behavior patterns. Thus, the DT can begin to draw some conclusions on its own based on the past performance of the asset.

d) **Level 3 (Predictive)**: Unlike the previous levels, this level of DT has the capacity to influence the future of the system. Through constant updates of the past and present state of the asset, this DT is capable of making continuous forecasts about its behavior.

e) **Level 4 (Prescriptive)**: This level incorporates what-if scenario analysis, providing recommendations based on these scenarios, as well as risk assessment and uncertainty quantification.

f) **Level 5 (Autonomous)**: This is the most sophisticated level of all. At this level, the DT can control the asset to redirect it to its optimal operating point if necessary, based on behavior analysis. Due to the limited maturity of this technology, there is still not full trust in this level of decision-making, leaving the final say to a human supervisor.

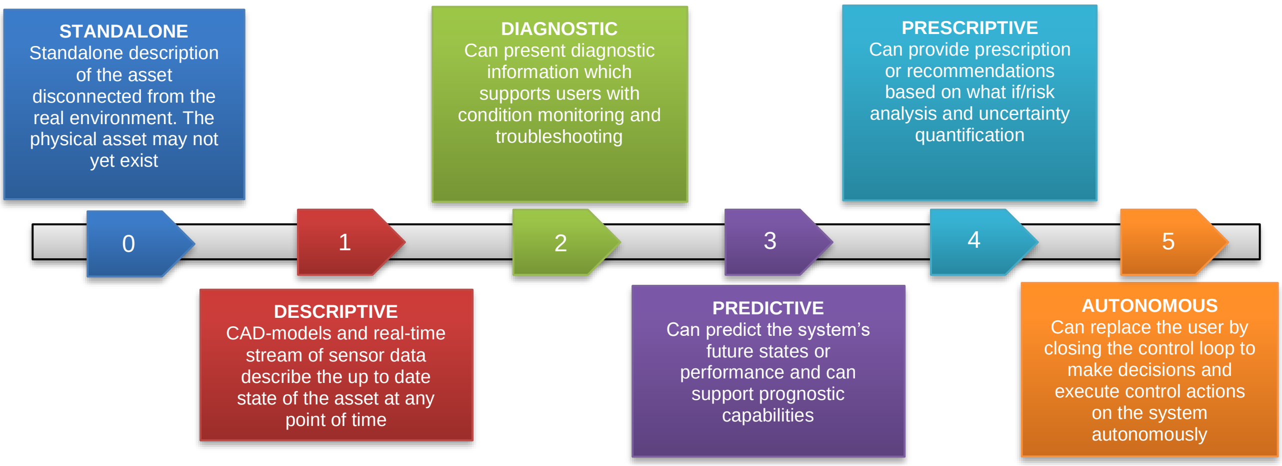

Fig. 12. *Levels of capability in DT (Adapted from (Sundby et al., 2021))*

5.2. Perspective from industry partners

Here we can see a summary of the responses from some industrial partners of NorthWind (Norwegian Research Centre on Wind Energy) to a survey about DTs conducted in 2023 (Stadtmann et al., 2023):

a) **4SUBSEA**: Although this company already extracts value from several DTs to determine strain and fatigue in some parts of an onshore wind farm, including a level 0 and a level 4, it maintains that its DTs cannot be more complex at the moment due to a lack of time and effort in system identification and digital model tuning. They also state that for a similar DT for an offshore wind farm, much more time and complexity would be require

b) **ANEO**: This company plans to use DTs to make decisions and predictions about the lifecycle of offshore farms. However, for now, they believe that human intervention is necessary before making the final decision. They maintain that many more daily operations that inspire confidence from the DTs are needed before entrusting them with any important decisions.

c) **COGNITE:** The goal of this company is to improve decision-making for any type of industry through DTs by combining data and simulations. They believe that efforts should be focused on developing and enhancing what-if scenarios.

d) **DNV MARITIME**: Although this company believes that in some cases it is sufficient to model only certain parts of the asset, they think that in the future it will be necessary to achieve more holistic digitalizations. They believe that the biggest challenge for DTs is end-to-end value chain support, as well as the lack of attractive business models for investors.

e) **EIDEL**: This company, with its regular customers in the space and defense sectors, aims to adapt its data acquisition system to meet some of the needs of offshore wind energy. Not wishing to build a DT from scratch on its own, the company believes that collaboration between investors and researchers is key to achieving effective DT development, as it sees aggressive information ownership policies as a significant obstacle.

f) **FORCE TECHNOLOGY NORWAY**: This company, capable of running what-if simulations but lacking real-time data streams, believes that the biggest challenges lie in the accuracy and reliability of automated finite element approaches and autonomous data processing. They believe that research should focus its efforts on hybrid modeling.

g) **KONGSBERG DIGITAL**: This company has access to a level 3 DT that it uses for an oil and gas platform, and aims to use DT for offshore as well. They are interested in optimizing maintenance operations using existing data, as well as using DT for induction and training. They maintain that the most important challenges to overcome are data standardization and autonomy in DT.

h) **KONGSBERG MARITIME**: At the moment, this company is focused on condition monitoring and condition-based maintenance, but they assert that predictive capabilities are the most important technology. They emphasize that industry acceptance, market adoption, and insurance company acceptance are the biggest challenges.

i) **SNSK**: This company is currently interested in DT for hybrid energy systems located in the Arctic and Antarctic, where besides cost reduction, minimizing maintenance trips to protect workers from the harsh conditions of these environments is crucial. Their proposal involves integrating wind turbines with other power production units and energy storage, with a focus on what-if scenarios.

j) **STATKRAFT**: This renewable energy company, the largest in Europe, is primarily interested in the descriptive and diagnostic levels of DT. They believe that the greatest challenge is developing and disseminating knowledge about building good DT software. They propose that research should focus on the steps prior to DT implementation.

k) **TOTALENERGIES**: This multi-energy company believes that it's not enough to model different parts of the asset separately; rather, it's necessary to unify the entire system into a single model, including drivetrain, electricity production, structural fatigue, and mooring tension. For them, the minimum level to generate value is level 1, although their goal is level 4. They also believe that it's necessary to minimize the number of sensors by optimizing their physical placement. From their perspective, the biggest challenge is integrating all the data from the different subsystems of the farm into one.

l) **EQUINOR**: This international company, committed to environmental goals of reducing carbon usage, envisions the asset's DT as a set of interconnected DTs, each focused on a specific use. They see open architecture and complete interoperability of information among industry members as necessary to achieve the full potential of DTs. This, of course, requires standardization of industry practices related to DTs.

CONCLUSIONS

The first conclusion I can draw from the research conducted is that we are facing a technology that is here to stay and that will bring about a revolutionary change in many aspects of our lives in the coming years. The increasing number and trend of annual publications on Digital Twins highlight the potential and projection of this technology, along with the growing interest of large companies in investing in this field. In the first part of the work, the history and evolution of the term are presented, and we find, as evidence of the exponential growth of interest in this field, the proliferation of definitions over time.

Conversely, this work highlights the immaturity of the technology, as reflected in the first chapter, where there is currently no universally accepted definition of what a Digital Twin truly is. Similarly, although not to the same extent, it presents the need for solutions to the major challenges faced by the offshore wind power generation industry. For this reason, Digital Twins are proposed as a solution to most of these problems, and a superficial explanation of their application is provided.

Following this, we provide a detailed list of reasons why DT technology cannot yet be fully implemented, whether in the offshore industry or any other field. From this list, the most significant challenge highlighted is related to data, including the associated subproblems such as cybersecurity. Another major issue that companies also emphasize is the decision to make data public or private. Making data private largely addresses the cybersecurity problem, but it poses a significant obstacle for a developing technology like DT. Therefore, it is crucial for investors and the scientific community to reach a consensus to ensure the continued growth of the DT field without major issues.

Lastly, we review a 2023 survey conducted with 16 major companies related to Digital Twins and the offshore industry. From this survey, we can identify the problems that investors consider most significant, which is a crucial aspect of technological development. As mentioned earlier, data issues are the primary concern because they are essential for the accurate functioning and realism required to clone a wind farm. Another conclusion we can draw is the need for research into hybrid modeling, as physics-based models are impossible to run in real time, and data-driven models fall short in terms of generalizability and reliability. Additionally, it is evident that Digital Twins need to be significantly more powerful, as companies intend to clone an entire wind farm as a single system rather than cloning individual parts. This, however, is currently impossible to achieve.

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