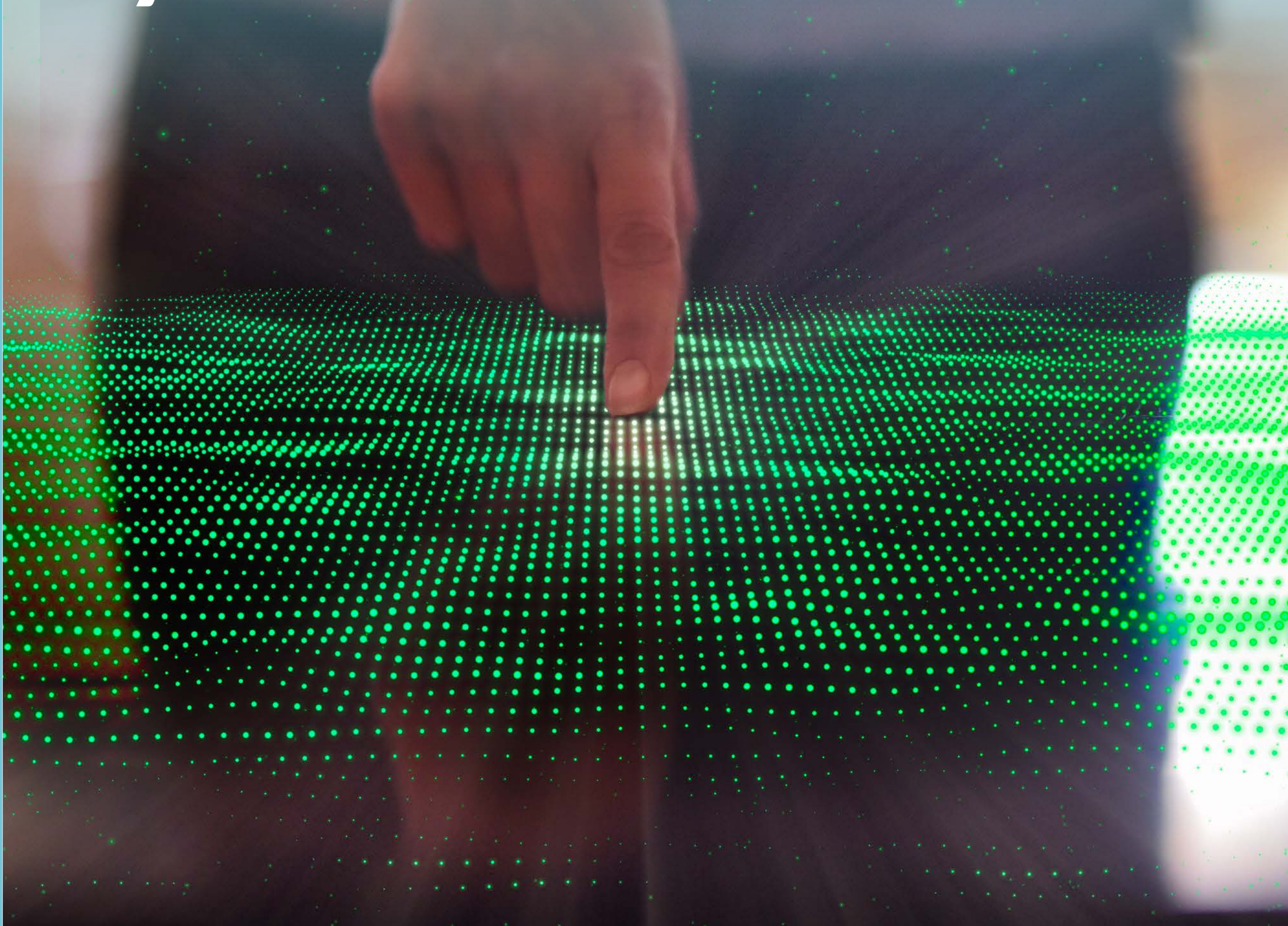
North Sea Energy
offshore system integration

5.2

North Sea Energy 2020-2022

Digitalization of North Sea Energy systems



North Sea Energy 2020-2022

Unlock the low-carbon energy potential North Sea with optimal value for society and nature

The North Sea Energy program and its consortium partners aim to identify and assess opportunities for synergies between energy sectors offshore. The program aims to integrate all dominant low-carbon energy developments at the North Sea, including: offshore wind deployment, offshore hydrogen infrastructure, carbon capture, transport and storage, energy hubs, energy interconnections, energy storage and more.

Strategic sector coupling and integration of these low-carbon energy developments provides options to reduce CO2 emissions, enable & accelerate the energy transition and reduce costs. The consortium is a public private partnership consisting of a large number of (international) partners and offers new perspectives regarding the technical, environmental, ecological, safety, societal, legal, regulatory and economic feasibility for these options.

In this fourth phase of the program a particular focus has been placed on the identification of North Sea Energy Hubs where system integration projects could be materialized and advanced. This includes system integration technologies strategically connecting infrastructures and services of electricity, hydrogen, natural gas and CO2. A fit-for-purpose strategy plan per hub and short-term development plan has been developed to fast-track system integration projects, such as: offshore hydrogen production, platform electrification, CO2 transport and storage and energy storage.

The multi-disciplinary work lines and themes are further geared towards analyses on the barriers and drivers from the perspective of society, regulatory framework, standards, safety, integrity and reliability and ecology & environment. Synergies for the operation and maintenance for offshore assets in wind and oil and gas sector are identified. And a new online Atlas has been released to showcase the spatial challenges and opportunities on the North Sea. Finally, a system perspective is presented with an assessment of energy system and market dynamics of introducing offshore system integration and offshore hubs in the North Sea region. Insights from all work lines have been integrated in a Roadmap and Action Agenda for offshore system integration at the North Sea.

The last two years of research has yielded a series of 12 reports on system integration on the North Sea. These reports give new insights and perspectives from different knowledge disciplines. It highlights the dynamics, opportunities and barriers we are going to face in the future. We aim that these perspectives and insights help the offshore sectors and governments in speeding-up the transition.

We wish to thank the consortium partners, executive partners and the sounding board. Without the active involvement from all partners that provided technical or financial support, knowledge, critical feedback and positive energy this result would not have been possible.

North Sea Energy offshore system integration

5.2

North Sea Energy 2020-2022

Digitalization of North Sea Energy systems

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Executive summary

Digitalization in relation to offshore energy systems is a topic of interest in the context of North Sea Energy (NSE) program. This report presents an overview on how digitalization can result in cost and emission reductions in the offshore energy sector. To this aim, nine digitalization technologies are reviewed and the potential barriers towards its implementation are highlighted. To showcase the potential benefits of a future NSE digital twin, simple examples based on possible components of such a digital twin are presented. A simplified case study using a dynamic simulator framework (TNO's PyDOLPHIN) illustrates the gains in optimizing component sizing and operational strategies, whereas a second example using AI methods highlights the importance of forecasting system boundary conditions (e.g., electricity demand) under uncertainties. Finally, the benefits and necessary steps to deploy digital innovations for the NSE are discussed using three reference scenarios. In particular, it is highlighted how digitalization will play a key role to achieve efficient operations, for predictive maintenance, and for how autonomous vehicles will assist in inspections, repairs, installation and decommissioning of assets such as wind turbines. This study was done as a part of WP5 logistics of the NSE 4 program but since the scope of the work was broader than only digitalization of the logistics and services, it was decided to deliver a separate report on this topic.

1 Introduction

The fourth industrial revolution is witnessing the use of various forms of digital technologies to manage industrial assets today (Porter & Heppelmann, 2015). First used at the Hanover Fair in 2011, the term 'Industrie 4.0', captured the attention of industrialists and governments worldwide. The objective of Industry 4.0 is to achieve a higher level of productivity and operational through automation and digitalization. It can be seen as a stimulus for several digital technologies, such as, big data, cloud computing, smart sensors, machine learning (ML), robotics, additive manufacturing (AM), artificial intelligence (AI), virtual reality (VR) and the Internet of Things (IoT). According to the report from McKinsey (Caylar et al., 2015), these digital technologies have high potential to significantly increase production productivity by 45–55% in technical professions. It integrates people, machines, and data, thus creating more efficient workflows.

According to Caylar et al. (2015), digitalization is to use automated processes and digital technologies to gather data in order to improve business outcomes. Øydegard (2017) pointed out the potential of digitalization in offshore wind through improved connectivity, efficiency, scalability, time savings, and cost savings for offshore wind systems operations. To the question: "*How are you using digitalization to cut costs?*", Edward Wagner, GM of Sentient Science responded:

"Digitalization is about getting information from the assets that we have, and using that information to drive the cost of energy downwards. Once you have digital information you can do supply chain integration, you can lower the cost of financing, you can improve O&M, but you have to be able to use the data to your advantage. This is a data driven application, we think only by having that data, simulating, doing what-if studies, and making sure you get it right before you actually climb that turbine to do work. Make sure you do it in a digital environment so you make sure you get it right before you do it (WindPowerMonthly, 2016)."

Subsequently, Michael Lewis, E.ON Climate & Renewables GmbH responded:

"For us digitalization is all about getting the right data so that we understand how our turbines are performing, how we can improve that performance, both in the short run and in the long run. And digitalization will allow us to have the right data, in the right time, in the right format so we can drive improvements in costs and performance (WindPowerMonthly, 2016)."

In this report, we will consider several digital technologies with the potential to support the offshore energy sector. Such technologies will be first reviewed in Chapter 2, where we provide definitions, examples from various sectors, and summarize the main barriers for digitalization. In Chapter 3 we discuss the first step towards a digital twin of the North Sea Energy system, providing an example of how a digital twin technology can be already used within the NSE context. In Chapter 4, we discuss promising digital innovations for the North Sea Energy system, highlight the opportunities for the integration of various technologies and the associated benefits. Conclusions are drawn in Chapter 5, where directions for future work are provided with the goal of fully achieving the Industry 4.0 revolution in the North Sea energy system. As a part of the activities, two workshops were organized together with the partners of the NSE program to identify the opportunities of digital technologies in the North Sea and the outcome of the workshops can be found in the appendix.

2 Digitalization potential for the North Sea

In this chapter, section 2.1 intends to review different digitalization technologies that could support the offshore energy sector and leading to possible cost and emission reductions. Barriers to digitalization are also briefly reviewed in section 2.2.

2.1 Digitalization technology review

This work will highlight the potentials of the following digitalization technologies:

- Digital twin
- Big data analytics
- Immersive technologies
- Industrial Internet of Things
- Robotics and automation
- Sensors
- Additive manufacturing
- Cybersecurity
- Data sharing

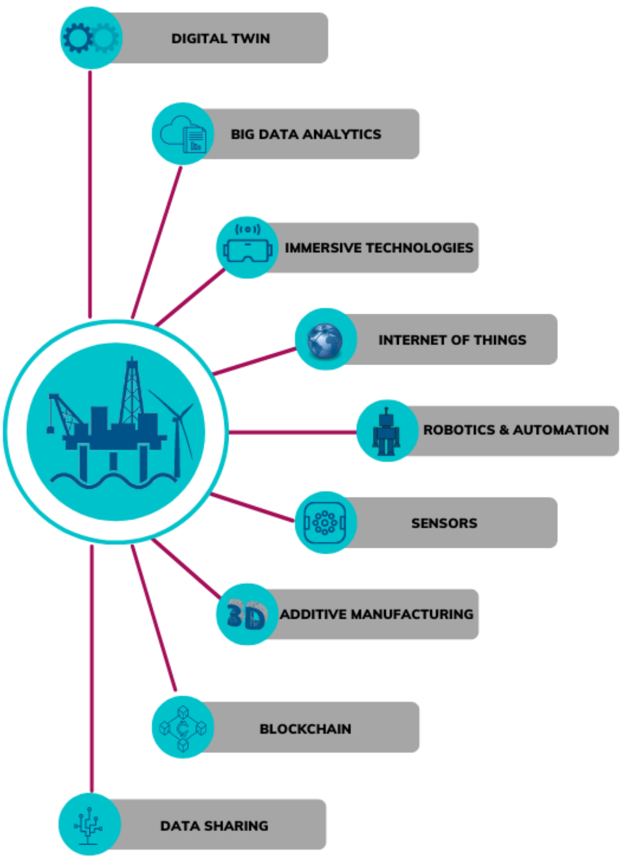
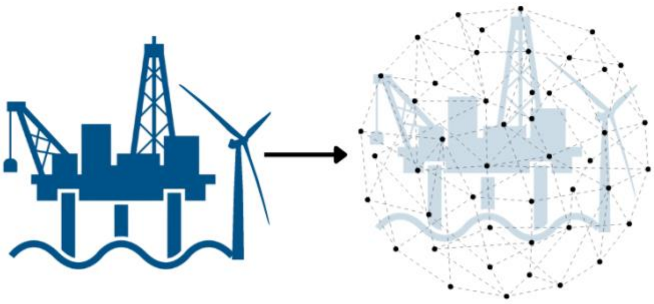


Figure 1: Schematic overview of the digital technologies highlighted in this report.

2.1.1 Digital twin



Broadly defined, a digital twin is a virtual representation of a physical object, asset or process. It can be used to gain new insights into the behaviour of such a system and to enhance performance. Typically, the components of a digital twin are (combinations of) models, data, computational methods, connection to the database and APIs, and possibly visual representations of the asset (e.g., CAD drawings). Models can be analytical, based on factsheets, physics-based, data-driven or based on machine-learning/AI. Data can be in various format (time-series, tables, logs) containing manufacturer specs, historical info, real-time values from sensors.

Depending on the level of integration with the physical asset, e.g., the flow of data to/from it, it is possible to distinguish between digital model, digital shadow, and digital twin (see Figure 2). A digital copy is not directly coupled with the physical counterpart. In a digital shadow the automatic data flow is only to the physical asset, without feedback. In a digital twin the loop of data exchange is complete. The scope of these digital technologies can vary from design of the asset, with digital models that can also be used before the physical counterpart exists, to real-time monitoring and control. Digital twins can be employed not only for diagnostics but can also allow to move towards predictive and prescriptive analytics, therefore achieving more difficult yet more valuable tasks (see Figure 3). The possibility of achieving different level of analytics (from descriptive to prescriptive) depends on the availability, accuracy and predictability of the models within the digital twin. Typical challenges for deploying the digital twin technologies are data management and security. In addition, processing speed and end-to-end visibility (clearly indicating the actions to the human operator, when the control is not fully automatized) are crucial for real-time decisions. Solutions to these challenges can be found in other digital technologies (such as cybersecurity) that will be also reviewed in this report.

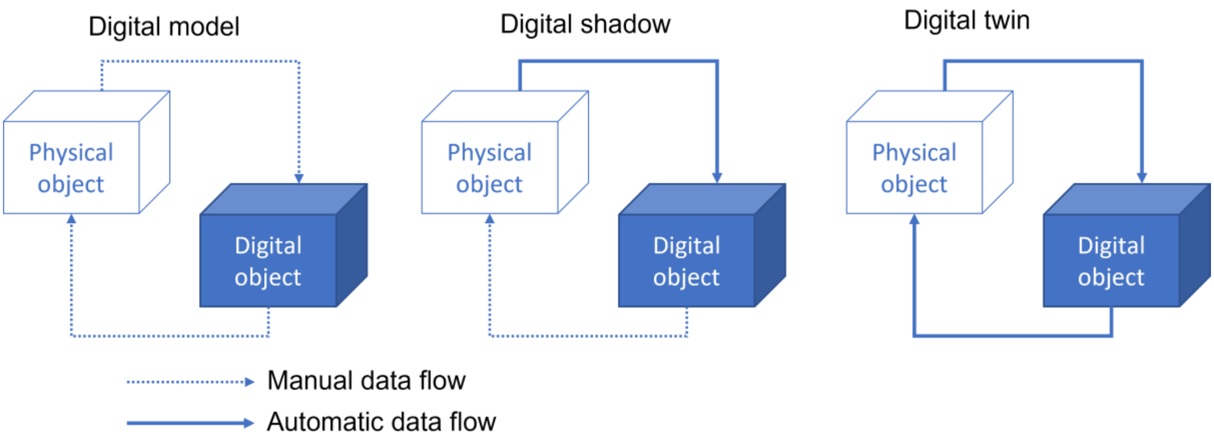


Figure 2 Differences between a digital model, a digital shadow and a digital twin is the data flow to/from the physical asset (Seppälä, 2020).

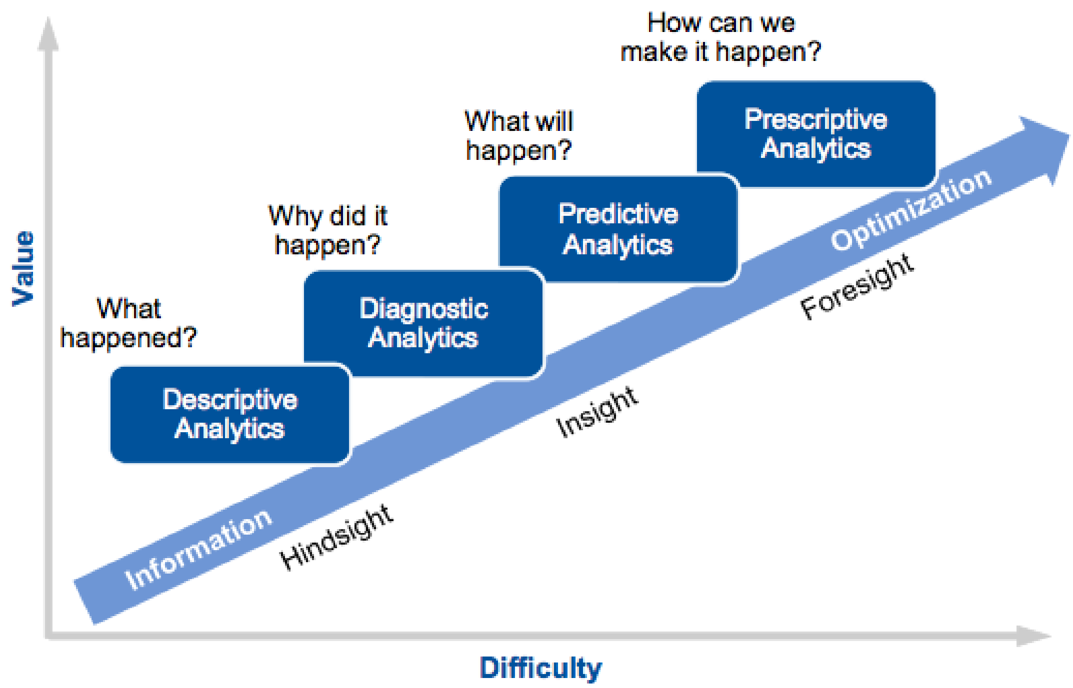


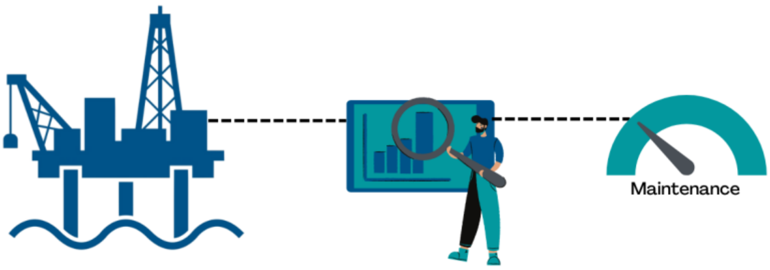
Figure 3 Gartner Analytics Ascendency model (Gartner, (2012), drawn from Schaap, (2020)). The more the sophistication of the digital twin the more the opportunities to execute tasks in the top right of the chart.

Within the current NSE project, variants of the digital twin technology (starting from the simpler digital model to a complete digital twin) can find a key role to achieve the goals defined in several work packages. For example, WP 1 of NSE 4 program focuses on the identification of energy hubs and the study of the required infrastructures. Once the most promising solutions have been identified, the use of digital models can further assess design feasibility and convenience. By taking into account different physical and economical aspects of the system, simulations of the system under consideration can be used to identify how to optimally size and connect different components in order to guarantee security of supply and to reduce investment and operational costs for all the operators involved. Such simulations can also quantify component and system efficiencies under dynamic loading, representing a way to assess the robustness of the design against possible (uncertain) scenarios. Different asset configuration layouts can be also simulated to compare, e.g. an offshore single large platform versus multiple smaller ones, or different ways of routing pipes and electrical cables. In the design phase, a digital model of the entire system, able to describe the physical response of the different commodities and the techno-economical necessities of the different operators, will allow to minimize the costs for all the actors involved and ensure the desired system performance.

Using the dynamic modelling capabilities of the digital twin for system integration will benefit also WP 6, that focuses on system mapping and modelling. Connections with WP 6 can be made both during the design phase to consider what-if scenarios or during operations to visualize the status of the system within the interfaces developed in WP 6. Moving from design purposes to monitoring during operations, a digital twin (or initially just a digital shadow) can be of use within WP 3 that focuses on safety, integrity and reliability. After calibration, the digital twin will be able to simulate the 'healthy' behaviour, that is in absence of any malfunctioning, of the entire system (or a specific individual component). Therefore, during operations, using the actual conditions as input, the digital twin will output the expected system behaviour. The digital twin output can be then compared with the real system behaviour measured by sensors, and the difference between the two can be an indicator of malfunctioning. Several AI techniques for anomaly detection can be coupled with the digital twin and a workflow for triggering warnings in real-time can be deployed to assist the operator in ensuring the safety and integrity of the system (Poort et al. 2020). Such tasks can be extended also to predictive maintenance. Similarly, the digital twin, informed by the sensor data, can be used within the context of optimally control the system, moving therefore from predictive to prescriptive analytics. For this purpose, the digital twin should be coupled with AI models for smart decision-making and optimizing future operations. Given the large importance of wind farms in the North Sea energy system, of particular interest it would be the ability of forecasting the wind power production and how the associated uncertainty propagates throughout the asset lines. Enhancing a digital twin with AI for forecasting under uncertainties can ensure reliable operations of the entire system, and therefore be beneficial for all the parties involved.

Apart from the digital twin of the energy systems, the development of digital twin for monitoring the ecology of the North Sea (WP4) and the logistics vessels trips (WP5) can assist in minimizing the impact of activities in the North Sea on the ecology and environment.

2.1.2 Big data analytics



Big data (BD) refers to voluminous sets of data. Data analysts attempt to extract meaningful insights from raw data that will be useful for decision making in different applications in industry. The term 'Big Data' defines the first characteristic of this method and that is the size of the available data set. There are other characteristics related to the data which make it viable to be classified under BD. IBM refer these characteristics as three Vs: volume, variety, and velocity (Dietrich et al., 2014). However, more recent articles have added two more Vs: veracity and value (Nguyen, 2018).

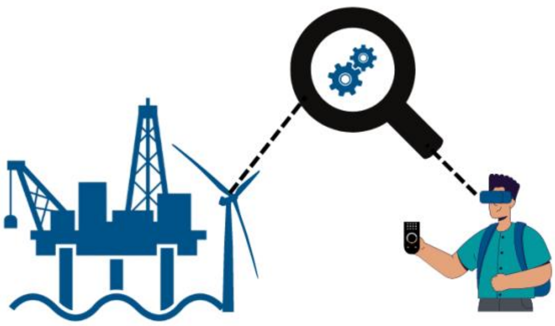
The amount and type of data collected and recorded in many industrial processes has greatly expanded, making meaningful extraction of BD a big problem. Equinor recently made operation data from the Volve Field on the Norwegian continental shelf public in order to help with BD learning challenges (Tunkiel et al., 2018). The total set of data for the Volve field production from 2008 to 2016 comprises of around 40000 files. The complete collection, which includes data from geophysical interpretations, the GeoScience OW Archive, seismic, well log, production, reservoir models, and real-time drilling data, is roughly 4,206 Gigabytes in size. Data on wind, weather, and the real-time performance of around 25,000 turbines worldwide is now being acquired and reviewed, according to Vestas (Chartron et al., 2018). Digitalization, according to Vestas, will aid in more exact weather predictions. Improvements in weather forecasting and analysis are one of the primary potential for O&M offshore wind cost reductions before 2025, according to IRENA (2020). In terms of risk assessments, Villani et al. (2018) advocates research collaboration projects on weather forecasts and artificial intelligence. In addition, digitalization and BD analysis can aid in the monitoring of vital key performance metrics. Chartron and Haasis (2018) suggested a technique for collecting pertinent data and analysing logistics inefficiencies during offshore wind park projects in order to discover improvement opportunities.

Several studies have been conducted in order to better plan offshore logistics activities, forming a blueprint for big data and real-time decision making analysis. For the installation phase, several decision support and simulation tools have been developed (Vis and Ursavas, 2016). More research has been done to optimize the vessel fleet throughout the O&M phase (Hu and Yung, 2020) and to use BD to improve offshore wind farm maintenance (Sperstad et al. 2016).

Adoption of big data analytics necessitates significant capital investments and concerted efforts at all levels of the enterprise, legal system, and government. Although the offshore energy industry is used to processing large amounts of data, combining BD analytics with existing systems presents a number of technological and non-technical hurdles. The use of current software tools and hardware computer platforms to efficiently deploy BD technologies is one of the technical obstacles. There is currently no perfect model of BD employment that promises a high profit enhancement while working within time and budget limits. The operation of the BD system also generates a number of challenges related to functionality, security, and maintenance. Cybersecurity, as a potential digitalization technology, will be presented in section 2.8. Collaboration amongst departments and parties to deploy and operate the BD system efficiently is another nontechnical challenge. Because of the breakdown in communication between the IT department and others, any issue, including such password resetting to access personal accounts of field workers, might take a long time to resolve. Implementation raises concerns at a higher level of innovation management, such as standards, data privacy, data ownership, and intellectual property rights.

Within the current NSE project, big data analytics can find a widespread use within the different work packages. In WP1, a big data approach can be applied to data from hubs, including time-series, design data in text and images, GIS data of locations of the assets, including cables and pipelines. In WP2, it can be discussed if and how big data should/could be applied to different documents within the NSE system, for example the use of Natural Language Processing (NLP) to derive context from legal data. Regarding WP3, AI can be applied to big data regarding asset/component reliability (both sensor data and simulation data), regulations, standards and guidelines. Similarly, in WP4 ecology data, such as emission data for LCA, could benefit from AI/big data methodologies. Furthermore, these technologies will be key for improving logistics (WP5), where there is abundant data related to vessels, ship manufacturing information, emission, scheduling and traffic. Finally, it could be possible to explore connections with AI and the NSE atlas developed in WP6.

2.1.3 Immersive technologies



Virtual Reality (VR), Augmented Reality (AR), and Extended Reality (XR) are names that are frequently used interchangeably, but their inherent technical differences, limitations, and application prospects must be better understood. These technologies, combined together, are pushing boundaries in terms of how we generate and consume information, allowing consumers to be engaged in a virtual world rather than simply watching it on a 2D screen. As a result, the term "immersive technology" is sometimes used to combine them all together. Immersive technologies, according to Gartner (Tan, 2019), include the utilization of information in the form of text, visuals, audio, and other virtual upgrades that are merged with real-world items in real time.

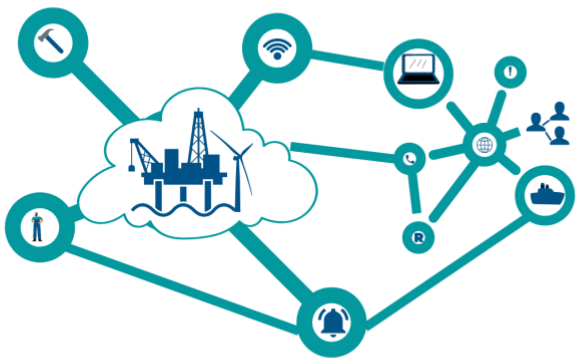
Immersive technology will allow for a seamless transition between the actual and virtual worlds, allowing for visuals to be superimposed over real-world objects like cables or fluids inside a turbine or an oil rig. Workers getting knowledge on how to replace a specific component simultaneously looking at the real system in need of repair is an example of this (Rüßmann, et al., 2015). They (2015) also discuss virtual training, wherein maintenance personnel are trained in various scenarios using a realistic databased 3D environment and augmented-reality glasses. Through virtual-representation as well as the ability to modify parameters and retrieve operational data plus maintenance instructions, operators will have a greater level of contact with machines using immersive technology. This appears to be an extension of simulation, with the most significant distinction being real-time data and the immersive effect of having this information in front of your eyes than on a screen. Microsoft HoloLens (Evans et al., 2017) allows for a multi-monitor experience, allowing users to quickly transitioning from a conventional working environment to a full sight of a turbine, for example, to learn, train, or control the turbine, and to also explore 3D in 3D. GE employs this technology in conjunction with a digital twin to illustrate that smart data on the company's products does not require being on site to make intelligent judgments (Wu et al. 2019). In the offshore wind sector, not having to go offshore to inspect, acquire data, or map conditions unless it's absolutely necessary is an attractive and economical solution. By properly utilizing this technology, one can ensure that you will be more prepared and that you will have completed all of your work obligations before travelling overseas. Another example is the Rolls-Royce Unified Bridge (Levander, 2016), a human-machine interface for ship operations that aims to minimize the operator's mental workload, improve workflow efficiency, and lessen the likelihood of accidents involving crew, vessels, or installations. One of the link of these immersive technologies with the current activities of the North Sea is the training of the operators or simulating the situations in which safety measures need to be practiced.

2.1.4 Sensors

Sensors embedded in components are nothing new; they are devices that are intelligent enough to recognize when something is faulty and have analytical capabilities. Blade sensors, vibration sensors, other embedded sensors, for example, are smart sensors that could recognize faults in an offshore system using data processing algorithms (Hall et al., 2013). With the use of sensors that collect data on a continuous basis via interconnectivity, the Industry 4.0 phase of industrial development makes things "smart."

According to Øydegard (2017), increasing the use of sensors on support transport vessels would result in a higher level of autonomy, which would improve workability, turbine availability, and fuel efficiency. Offshore wave conditions typically result in a 'grey' region in the operating window for Crew Transfer Vessels (CTV) between 1.2m and 2m of substantial wave heights. The probability of such marginal weather window occurring, according to BMO offshore (Dewan and Asgarpour, 2016), is projected to be 30%. External vessels are paid to perform in this narrow operating window, however due to a lack of vessel performance data for marine control, a best-practice 'no-go' decision is made at substantial wave heights exceeding 1.2m. During this weather window, it is expected to see a 25% increase in deployment. Furthermore, according to BMO offshore, vessels are frequently cruising at maximum speed to maximize technicians' work time. Technicians are anticipated to return to port after working less than 12 hours on 65 percent of days. In certain cases, vessel speeds might be reduced from 25/26 knots to 20 knots. The resulting fuel consumption can only be reduced on the inbound and return legs; the outgoing leg cannot be reduced. As a result, a sensor that alerts the crew when it's time to slow down might save money on fuel. In addition, new developments in the sensors to measure gas quality, leakages and process conditions when an integrated energy system will be operated, will provide new insights to the operators of the production and transport systems to track and monitor the system behaviour in real-time and detect anomalous behaviour in time. New sensor developments are required to ensure an efficient and reliable operation of the energy systems.

2.1.5 Internet of things

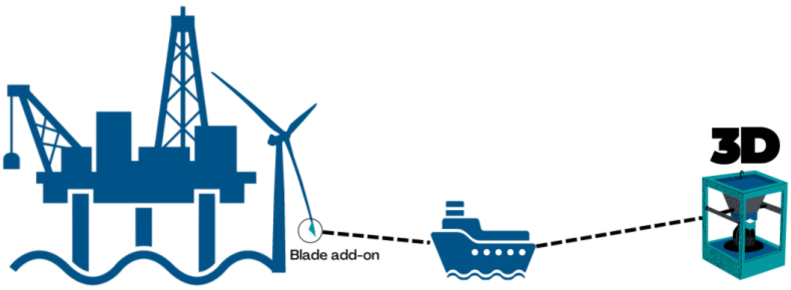


Meola (2016) describes the Internet of Things (IoT) as a network of internet-connected items that can collect and exchange data via embedded sensors. IoT allows for significant data collection, enhanced connectivity, as well as the extension of digitization, digitalization, and connectivity to previously analogue jobs, processes, and operations. According to Iansiti and Lakhani (2014), there are three key qualities that explain why the IoT is altering enterprises. To begin with, unlike analogue communications, digital signals may be sent flawlessly. Digital signals, on the other hand, can be repeated forever. Lastly, once the network infrastructure investment has been made, it can be transmitted to the incremental consumer at no cost.

In 2012, GE coined the term Industrial Internet to differentiate between the industrial and consumer levels of IoT (Leber, 2017). The Industrial Internet of Things (IIoT) or the Industrial Internet, according to GE, can be thought of as connecting equipment and devices in industries where even more is at stake, or where breakdowns and unscheduled downtime might result in life-threatening or high-risk situations. According to IBM (Dietrich, 2014), intelligent machines, facilities, fleets, and networks are converging with advanced analytics, predictive algorithms, and automation. These linked machines can teach, for example, offshore system operators how to boost productivity or identify a failure before it happens, allowing different units to collaborate to support better intelligent design, operations, maintenance and safety. According to Inductive Automation (Vavra, 2016), IIoT may considerably increase interconnectivity, productivity, scalability, time savings, and cost savings for offshore enterprises via predictive maintenance, greater reliability, and operational efficiencies.

IoT allows for the identification of every individual good throughout a supply chain, allowing for end-to-end visibility by quickly reporting both item status and condition in offshore logistics (Tadejko, 2015). Shipment, inventory, warehousing, quality assurance, maintenance, security, safety, and reverse logistics procedures all benefit from this capacity. Monitoring the status of products in transit (e.g. temperature, humidity) using IoT technologies (e.g. radio frequency identification system) can help with delivery scheduling. The usage of telematics-enabled vehicles can boost the transfer vessels and personnel (Andersson & Jonsson, 2018). IoT improves item traceability across the supply chain, making it easier to identify suppliers who are accountable for quality issues (Georgakopoulos et al., 2016). It reduces time by easing item identification and improving order picking routing, resulting in improved warehouse operations and inventory accuracy. Thefts, shrinkages, and unlawful efforts to access restricted areas are all detected by IoT (Fan et al., 2015). Devices can detect driver fatigue levels or signal warehouse employees mistakes/errors, for example, and IoT improves working conditions by improving safety (i.e. minimizing errors). Georgakopoulos et al. (2016) stated that IoT can also help employees perform better by offering task suggestions. IoT warns retailers of inventory levels and replenishment times in inventory planning. At the same time, IoT technologies improve consumer happiness by allowing them to follow their orders in near real time. Organizations can also give more tailored logistics services by using the digital trace and locational data of items via IoT. Furthermore, real-time data on product and asset usage enables for more effective reverse logistics planning and predictive maintenance (Ben-Daya et al., 2017).

2.1.6 Additive manufacturing

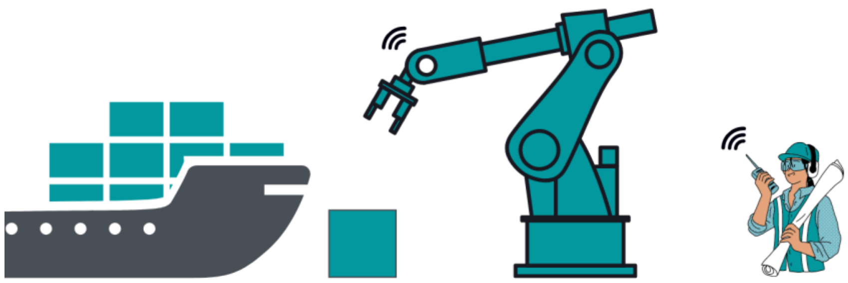


Additive manufacturing, also known as additive, digital, or fast manufacturing, can create objects that has been digitally designed as a three-dimensional model (Rogers et al., 2016). 3D printers can use recycled materials to create high-quality goods with the least amount of trash and materials (Pakkanen et al., 2017). By diminishing the scope and scale advantages of conventional production methods, 3D printing technology can achieve mass customisation (Sasson & Johnson, 2016). On 3D printing, there are two different perspectives: the first is that 3D printing is a revolution that will cause traditional production techniques to be disrupted (Mohr & Khan, 2015). On the contrary to disrupting the traditional production methods, 3D printing would only enhance the existing methods (Sasson & Johnson, 2016). Regardless of the differences, both arguments agree that 3D printing will have a substantial impact on the global value chain and logistics operations.

3D printing would allow for localized production close to offshore sites and is predicted to eliminate some supply chain stages (e.g. second-tier suppliers). Such localized and portable production will enable businesses to enter areas that are currently closed to them due to logistical constraints, such as long distances and risks (Sasson & Johnson, 2016). Furthermore, due to shorter lead times and the potential to deliver higher levels of customization, localized production will improve logistical service quality. Furthermore, 3D printing-enabled near-sourcing (i.e. localized production) is predicted to lower shipping costs, safety stock levels, and import/export logistics expenses. Decentralization of distribution facilities and warehouses will reduce the requirement for inventory of semi-finished and finished goods; instead, raw materials feeding 3D printers, such as plastic, metal, and ceramic, would require inventory. This transition will reduce the number of stock keeping units required (Rogers et al., 2016), lowering inventory carrying costs, eliminating assembly activities (i.e. lowering handling costs), and cutting the number of vendors engaged directly (i.e. decrease sourcing costs).

In three ways, 3D printing technology will improve the efficiency and efficacy of reverse logistics operations. Firstly, involving customers in the design and production stages will reduce product returns. Secondly, the reduced trash generated by 3D printers will lessen the requirement for garbage collection and processing (Sorkun, 2018). Lastly, on-demand 3D printed spare parts decrease inventory-carrying costs while reducing customer wait times. Mercedes-Benz Trucks, for example, now uses 3D-printed spare parts for this reason. Similarly, the start-up Fast Radius has set up a 3D printing facility near UPS to facilitate faster product returns (Ryan et al., 2017).

2.1.7 Robotics and automation

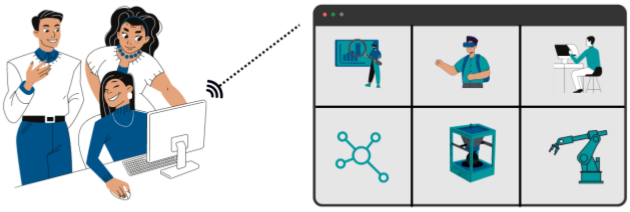


Organizations are investing in automation and robots as a result of increased competitiveness and technological advancements. In industrial automation applications, a robot is described as an automatically controlled, reprogrammable, multipurpose programmable electromechanical device that is either fixed in situ or mobile (IFR, 2018). Automation is speeding up as the fourth industrial revolution unfolds. Robots begin to interact and communicate with other devices, materials, and industrial components in smart factory systems.

The benefits of utilizing specialized robotics for maintenance were suggested in Made Smarter (Maier, 2017). As an example, wind turbine blades are difficult to access. Øydegard (2017) investigated the use of autonomous vessels and drones for inspection and access. Stein (2018) looked into the use of Unmanned vehicles for inspection activities in the maritime environment. He claims that this innovation lowers costs and increases the efficiency and safety of operations. A further contribution by Stein (2018) expanded on the usage of the United States in maritime and port security operations. Inspection that would prevent staff transfers on the offshore ports, and therefore avoiding the typical CTV or helicopter transport would be cost effective. Similarly, minor replacement parts or tools are transferred from the installation vessel deck to turbine nacelles. A missing tool or spare part during installation can cause delays. A technician must climb from the installation vessel deck to the nacelle to deliver a spare part or tool to the top of a turbine, which takes roughly 20 minutes in an elevator or a minimum of 30 minutes climbing. Such operations can be carried out by the unmanned vehicle in a matter of minutes.

According to the International Federation of Robotics (Klump et al., 2021), 2.1 million new automation robots will be in operation around the world by 2021, reflecting a 14 percent annual growth rate between 2018 and 2021. Robotics installation rates are 10% in Europe, 13% in the United States, and 16% in Asia.

2.1.8 Cybersecurity



Cybersecurity is currently receiving a lot of media attention, and its importance will only grow as more of the industry and the world population become digital. It is critical that software connected to the discussed digital technologies has a high level of safety and security built in it. For example, in order to build cloud technology, there must be confidence in the cloud solution's safety and integrity. Increased connectivity across assets and the system, as a result of step two of the digitalization method, may result in isolated cybersecurity solutions between the systems. This could allow weaknesses to be exploited, necessitating the allocation of extra resources to this activity in order to prevent cyberattacks and accidents. Avoiding any intrusion into these cyber systems would need to be a top focus at the highest levels of the architecture, where machines may make decisions and have increasing control. If the scenarios and estimates for offshore wind's rising part of the entire energy mix come true, a cyberattack that causes a shutdown or disconnection from the grid might have serious implications. Throughout the digitalization process and beyond, cybersecurity would need to be maintained and developed.

The maritime space's esoteric nature, along with a general sea blindness in which the maritime space is badly undervalued and often disregarded, makes it an ideal target for cyberattacks. Due to the lack of continuous surveillance and speedy response, the chance of being caught in the maritime sector is far lower than on land. There have been instances where port records have been altered to conceal full oil tankerloads. Ships can, in other words, call at a port, load up with cargo, and then leave with no record of the transaction. The energy industry must be proactive in creating strategies to reduce the scope of crime, particularly theft, that could occur within the marine domain, given the range of criminality that could occur. A cyberattack on OT in the ICS on a ship in the energy sector, or on the operation of an offshore plant, might cause major problems. An operational strike could include anything from causing a ship to use more fuel to shutting down the electricity on a vessel or rig to pressurizing a pipeline to the point of rupture. Ports have also become a major source of worry. While many of the systems at a port are vulnerable to IT attacks—and there have been numerous cases of both ransomware and virus incidents, the OT at ports is rapidly becoming a target for hackersIn June 2020, for example, the OT systems of Iran's Shahid Rajaee Port were targeted, causing maritime turmoil and halting tanker flow. According to a related analysis conducted by Lloyds of London, insurance firms would be unable to cover the costs connected with a breach of OT systems in fifteen Asian ports, with a potential damage of $110 billion.

The energy sector must be aware that indiscriminate cyberattacks could have a negative impact on its maritime assets at any time. An offshore rig or an entire offshore wind farm could be shut down by a ransomware or malware attack, for example. To mitigate and respond to threats, protocols and response mechanisms are required. Companies that have gone through similar crises can teach us a thing or two.

While the energy and maritime sectors are notoriously competitive, security is not an area where any legitimate player gains from competition.

2.1.9 Data sharing

Data sharing is a cornerstone of digitalization, and some ways of exploiting data sharing have already been discussed in the previous sections. In this section, we focus on innovative technologies that allow data from different parties to be harnessed without compromising privacy and confidentiality. Two examples are multi-party computation (MPC) and federated learning (FL). In MPC, data are shared, whereas in FL insights are obtained without sharing data. Secure MPC consists in using advanced cryptographic techniques to enable computations on sensitive data from multiple parties, without sharing or revealing this data. Key aspects are to maintain privacy (private inputs remain private) and to guarantee correctness of the output. Nowadays, a collection of cryptographic techniques is becoming more mature (homomorphic encryption, secret sharing, garbled circuits, zero-knowledge proofs, …) and the optimal solution will depend on the application scenario. Federate learning (FL) is a machine learning technique that trains a model across multiple decentralized devices holding local data, without sharing the data. The model is trained locally based on own data that will not be exchanged with the other parties. The model parameters from the local models are instead exchanged and the global model can be updated. All users can then benefit from the updated model.

More broadly, synthetic data generation can also be part of the data sharing process. First of all, shared databases can be enhanced by new data which are generated by appropriate machine learning algorithms, such as generative adversarial networks (GANs), that allow to construct variational models. Such models can then be used to generate new datapoints based on different input parameters that can be representative of different operating conditions not contained in the initial dataset. The augmented dataset can be then shared and used by different parties. Alternatively, each party could perform the synthetic data generation locally and provide the synthetic datasets to the other parties, in order to share representative information of the local data but maintaining the privacy of the original data.

Within the current NSE project, data sharing can find a prominent role in the activities defined in several work packages (WPs). For example, data security and sharing regulations should be considered in WP 2 that focuses on society, governance & communication. Both MPC and FL are technologies that should be considered and requirements for the applications within NSE should be defined before deployment. Defining efficient, reliable and secure procedures of data sharing during operations can be key to ensure optimal offshore logistics, that is the focus of WP 5. Synergies between data sharing and visualization tools can be also investigated within WP 6, that focuses on system mapping and modelling. The developed ATLAS tool can be connected to a system of data sharing as a first step towards an illustration tool to be used during operations and potentially connected with a digital twin framework as well.

2.2 Barriers to digitalization

This section examines the barriers towards the implementation of digitalization in the offshore energy sector. A comprehensive literature review, followed by discussions with industry experts, identifies seven most prominent challenges, which are:

2.2.1 Value-chain integration

In order to accomplish the seamless integration of different digital technologies, Caylar et al. (2015) investigated the challenges of reducing barriers between various organizational units. The issue gets considerably complex when multiple companies along the value chain need to integrate. Pérez-Lara et al. (2020) stress the significance of close collaboration among value-chain partners as well as horizontal value-chain integration. Dalenogare et al. (2018) argue that the lack of IoT integration in an Industry 4.0 scenario is another reason why most enterprises fail. They argue that the non-technical challenges that the IoT (and subsequently digitalization) faces still require workers with the necessary knowledge and abilities. According to Breunig et al. (2016), many businesses acknowledge that they lack the necessary knowledge or skills to fully utilize the digital technologies.

2.2.2 Ensuring data quality

Four characteristics of good data are consistency, completeness, correctness, and redundancy (Chen et al., 2014). Organizations would need to be networked in the fully realized big data era, which would generate enormous amounts of data that are impossible to test for completeness and data integrity due to their complexity and variety. Consequently, there is also a greater possibility of making a mistake. Additionally, when data is shared among many contributors and changed frequently, it becomes extremely challenging to maintain data consistency and integrity. Considering organizations will be much more networked than they were in the past, ensuring high data quality will remain as a major challenge.

2.2.3 Security breaches

Concerns regarding the dangers and risks of data sharing among value-chain partners are raised by interconnectivity (Geissbauer et al., 2016). Breunig et al. (2016) examine fear among enterprises of losing their data to third-parties in addition to their worries about cyber-security. Given that Lee and Lee (2015) see hackers as one of the potential issues with IoT adoption, security breaches would be a serious concern.

2.2.4 Low technology maturity

The potential for instability while deploying unproven, early-stage digital technologies is presented by Lee and Lee (2015). Although there are now more untested digital technologies, there may be an imbalance in some technologies with regard to standards, privacy issues, and data security. According to their study, even though this might not seem like a major concern in a disconnected environment, it might have a significant effect on a centralized network of technology.

2.2.5 Lack of standards, regulations and certifications

According to Schröder (2016), the absence of defined standards and regulations causes small and medium-sized businesses (SMEs) to have reservations about adopting digital technologies. According to Schröder, SMEs find it challenging to participate in networks and activities that create value because there are no standards in place. Additionally, as technology develops, authorities and legislators struggle to protect the interests of customers even when they cannot keep up with the rapidly changing technology and its widespread effects. Authorities must therefore quickly adapt to the evolving technological breakthroughs in order to comprehend what they are regulating (Schwab, 2017). In addition, standardization of data currently is under development and this will be an additional barrier for the organizations to deploy digital technologies.

2.2.6 High investment

Organizations seeking to implement digital technologies must commit to double their estimated annual capital spending for the coming five years, according to Geissbauer et al. (2014). To achieve digitalization goals, this not only calls for a re-engineering of current strategies, but also for a large investment. In addition, Kache and Seuring (2017) support this claim by adding that large investments in people, processes, and technology are needed at both the corporate and supply chain levels. Breunig et al. (2016) claim that despite the significant financial requirements, most organizations are still reluctant to participate in R&D connected to digitalization. The productivity gains and financial advantages of investing in digital technologies have always been contested (Caylar et al., 2015). It is challenging to make a trustworthy estimate of the economic benefits of digital business due to the productivity paradox in technology implementation.

2.2.7 Job market

According to Schwab (2017), organisational digitalization would increase inequality and may disrupt the job market. Conflict will result from the market's division into low-skill/low-pay and high-skill/high-pay sectors (Schwab, 2017). Additionally, it is asserted that digitalization will increase inequality by strengthening the gap between those who depend on digital technology and those who depend on labour, while benefiting intellectual property owners and their shareholders.

Table 1 – Summary of the main potential barriers to digitalization.

Potential barriers	Challenges	Technology focus/solution
Value-chain integration	Stakeholder collaboration, physical and digital integration of infrastructures	Sensors, Industrial IoT, Data sharing
Ensuring data quality	Define, acquire, exploit meaningful data	Sensors, Industrial IoT, Big Data analytics, Digital twin
Security breaches	Protect data and protocols	Cybersecurity, data sharing
Low technology maturity	Advance low-TRL solutions, scale-up pilot projects	All
Standards and regulations	Identify common frameworks in fast-evolving technologies	All
High investment	High investment needed, demonstration of added value in integrated chain	All
Job Market	Lack of digital skills	All

3 Towards a NSE digital twin: case study

In this section, some of the main components that would lead to one of the digital technologies proposed before, a NSE digital twin, will be showcased. A technology description of how a digital twin could be used is given, followed by a MVP (minimum viable product) via a case study is presented. This MVP aims to highlight the advantages of the combination of digital technologies even for a very simplified system.

3.1 NSE Digital Twin technology description

A North Sea Digital Twin (or a collection of Digital Twins for each asset) can be composed of several different technologies. Figure 4 shows an example of a digital twin for a system comprised of green hydrogen production via electrolysis connected to a wind park. On the left side of the graph, it can be observed that four elements act together in this example:

- Dynamic physical modelling: a modelling framework can be used to create a digital copy of an existing/future asset, to calculate the dynamics at system/component/subcomponent level when connecting different energy sources, conversion, transport and storage options. An example used in the case study of the next section is TNO's PyDOLPHIN simulator.
- Automated systems to provide flexible, robust and user-friendly ways of testing multiple configurations and setpoints for exploration and knowledge-gathering purposes.
- Model enhancement and validation via experimental data. In addition to traditional calibration techniques, data-driven/AI models can be used for flexible calibration.
- Optimization/control algorithms for design and operational purposes, allowing for smart decision-making purposes that can be tailored to a plant or larger assets, such as a multi-commodity system connected to a network.

Depending on the level of fidelity and the integration with other elements (such as hardware/EMS systems), different levels of digital twins can be constructed. Ideally, this collection of digital twins, being tailored to each specific problem, should be able to communicate with each other. A standard modelling language, such as TNO's Energy System Description Language (ESDL), could be used for this purpose.

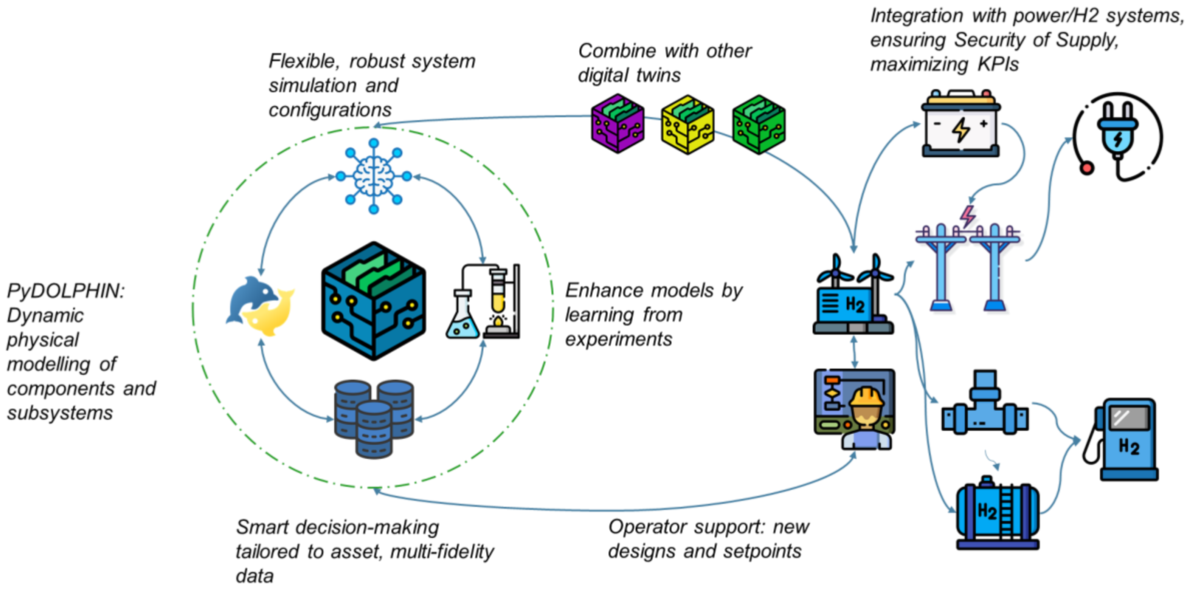


Figure 4: Representation of a Digital Twin for the North Sea, with TNO's PyDOLPHIN as a simulator, assisted by AI models for smart decision-making and optimization.

3.2 Dynamic physics simulator (digital model): PyDOLPHIN

In the following case study, TNO's PyDOLPHIN physics-based simulator will be used to model the different component and their interactions. PyDOLPHIN is a framework that allows to perform simulations of multi-commodity assets and obtain energy flows, efficiency, load factors and constraints at component and system level. In addition, it can be customized to perform techno-economical calculations (CAPEX, OPEX, LCOE, LCOH). The reason to use a dynamic simulator is that static modelling/optimization of assets that contain variable energy sources, transport, storage and conversion elements can lead to suboptimal/infeasible design and/or operation. Figure 5 shows a simplified example of an infeasible asset design. In this case, only averaged supply and demand (left) were considered, obtaining an optimum sizing of the different components. However, in practice, the dynamic nature of supply/demand combinations depleted the H2 storage in less than 9 months (right plot). Hence, despite the asset line was found suitable using static calculations, the dynamic simulations showed how it was in fact inadequate.

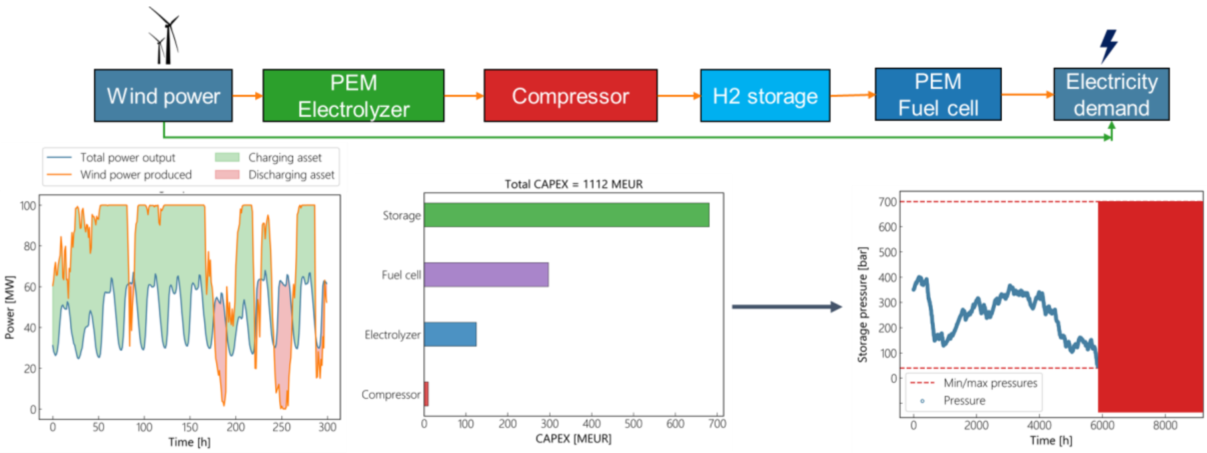


Figure 5: Example of asset design considering only static efficiency and supply/demand averages. A dynamic simulation that explicitly consider the variability in supply/demand and component dynamic efficiency/responses shows that the designed asset line is in fact not suitable (the storage gets depleted and therefore security of supply is not guaranteed).

Dynamic modelling in these situations becomes relevant even in exploratory phases. Figure 6 shows the use of PyDOLPHIN in the same case, optimizing the sizing of different components, with the goal of minimizing CAPEX while keeping the H2 storage levels between min/max bounds and as close to the initial point at the end of a 1-year simulation. The boundary conditions are the same wind power curve, with three demand curves which share the same mean demand but different levels of variability. For static modelling, the three optimum designs would be identical, as no variations would be considered. However, it can be observed how the digital copy of a potential optimum system can show **variations in CAPEX of up to 58% depending on the demand dynamics**. In addition, for the case with the highest variations, even an oversized system with respect to the baseline case will likely not work for a longer period of time: the H2 storage was close to be depleted after a single year. A different type of asset or boundary conditions would then be needed (e.g., combining a smaller battery or aiming to provide H2 in peak-shaving). A digital copy with fast and accurate modelling can provide insights in current assets (for operational purposes) and future ones (for design problems).

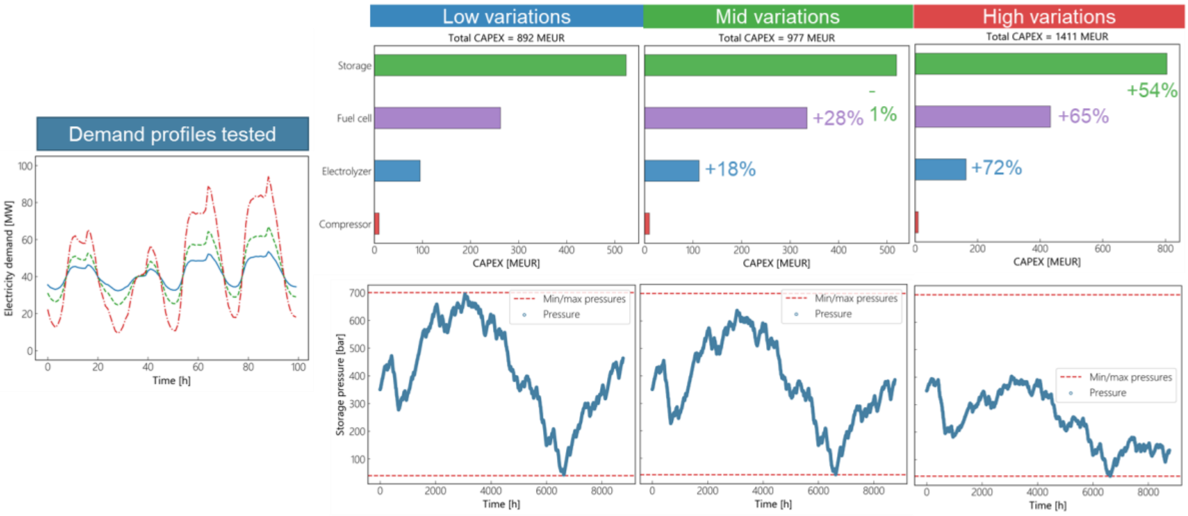


Figure 6: Optimum results obtained by PyDOLPHIN of the same system using three different demand profiles, for a fixed wind power curve.

3.3 Case study definition

To illustrate some capabilities of a future digital twin of an energy system in the North Sea, a simplified design optimization problem is considered. Figure 7 shows the configuration tested, for different boundary conditions. The design optimization problem comprises 2 types of assets/actors, which could theoretically act either independently or together. The actors are two wind farm operators (1.5 and 0.5 GW, respectively) and two new electrolysis plant operators, with a maximum of 800 MW for the two electrolyzer systems. It is assumed that both wind farm operators act together, with a similar assumption for the electrolysis operators. Platform(s) are considered to be available, with sufficiently close electrolysis systems to the wind power. The wind power profile corresponds to 2017 simulations of a North Sea wind farm in TNO's FarmFlow tool. Electricity prices are scaled ENTSO-E prices from 2017 to reflect 2022 projections, and hydrogen prices are a synthetic curve with periodicity of 1 week.

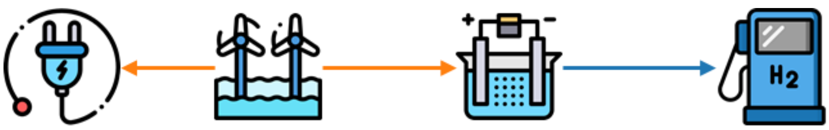


Figure 7: Configuration tested

The goal of the optimization problem is to **find the optimum electrolyzer capacity to maximize the combined profit of selling electricity and hydrogen,** given the fixed wind farm configurations. The profit is calculated based on wind farm costs corresponding to values given for Hollandse Kust West in Lensink and Pisca (2019) and projected PEM electrolysis values in 2022, with a 1-week period synthetic sinusoidal curve. This study aims to provide a qualitative overview of the effects of different price dynamics and asset operation on the optimum design, highlighting that different boundary conditions and projections can lead to very different systems as well. The cases that have been run aim to model the effect of several digital technologies and collaboration: optimum design via digital twin physical modelling, smart production/operation and combination of several actors vs a single actor.

3.4 Results

In this section, the results for different tests of the system are shown. In the graphs and tables, the optimum configurations are shown. Unless explicitly specified, the baseline case to be compared with is an electrolyzer set to the mid-range of the allowed capacities (425 MW).

3.4.1 Optimum design via accurate physical modelling (digital model)

The first digital technology that is showcased is the physics-based digital copy of potential new systems. By using models that take into account the dynamics of multi-commodity energy assets, optimum configurations can be found that can withstand the constraints of a variable power source, such as offshore wind. Figure 8 shows the results of optimum electrolyzer sizes with respect to H2 prices. In this set of simulations, the asset logic is set to produce and sell as much hydrogen as possible to minimize electrolyzer start-ups/shut-ins. It can be seen that the optimum size can be widely different depending on the boundary conditions, and that for this specific set of cases, the variation is quite steep. Due to this, it can be highlighted the importance of having accurate models that represent the different parts of the system, including its boundary conditions.

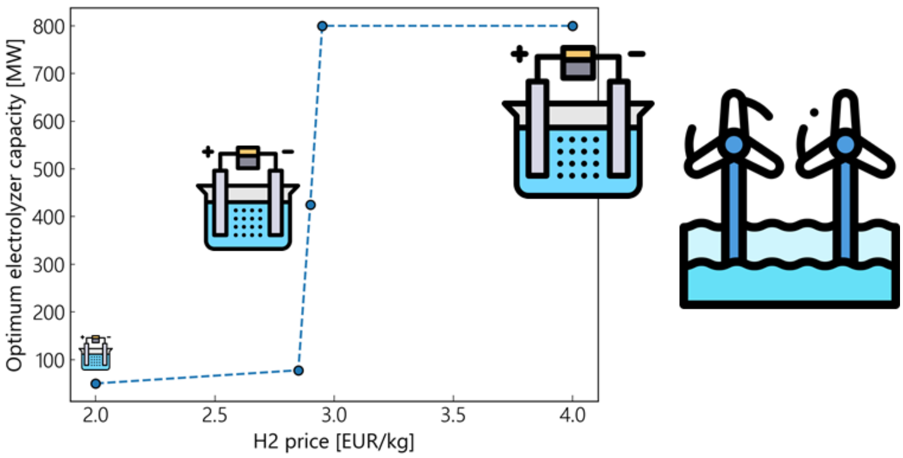


Figure 8: Optimum electrolyzer sizes with respect to H2 prices for a fixed electricity prices dataset. Area of each icon scaled to the capacity/production per case.

Table 2 shows the profit gain via optimum design and accurate modelling of the system. It is observed that the gains, even in a simple system, can be significant, being around 4% at the lowest and highest H2 prices tested. It should be noted that there are certain conditions where a baseline design is good enough, and no profit is gained via a posterior sizing optimization, as shown for a mean H2 price of 2.9 EUR/kg.

Table 2: Profit gain via optimum sizing design for multiple H2 prices.

H2 mean price [EUR]	Optimum electrolyzer size [MW]	Profit gain via optimum design [%]
2.0	50	4.0
2.9	425	0.0
4.0	800	4.2

A digital twin of the system with the ability of predicting performance for a wide array of operating conditions can also provide information about future levels of efficiency of the components. Figure 9 shows efficiency distributions for the optimum electrolyzer size in each of the cases. It can be observed that due to the mismatch in scale between wind farm size (2 GW) and electrolyzer (50-800 MW), it operates at a slightly lower efficiency than its optimum (closer to 0.70). This optimum is obtained at a lower load. Future systems with novel configurations, such as in-turbine electrolysis and very large-scale plants could potentially be controlled to lower the energy losses associated with the conversion process.

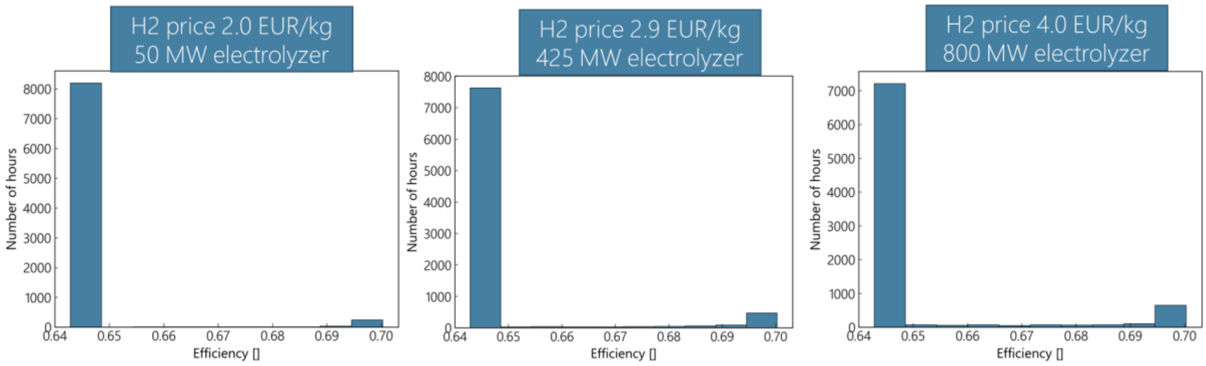


Figure 9: Efficiency distributions for optimum electrolyzer sizes. The asset logic consists in always producing as much H2 as possible.

3.4.2 Smart production/operation gains

In this section, different ways of operating an existing asset are explored. The previous baseline case is compared with a *smart production* strategy. Figure 10 illustrates how the term is defined in this simplified case. In the bottom plots, the price per kW of electricity and hydrogen are shown. With the previous strategy (produce and sell as much H2 as possible), there are several instances where it is not the most profitable option. Instead, an automated system that can provide insight of which technology to produce/sell and allocate the different energy sources can result in an improvement of the profit obtained. In particular, the left plot of Figure 10 shows an improvement of 19% in the effective mean price per kW of the commodity sold via smart production.

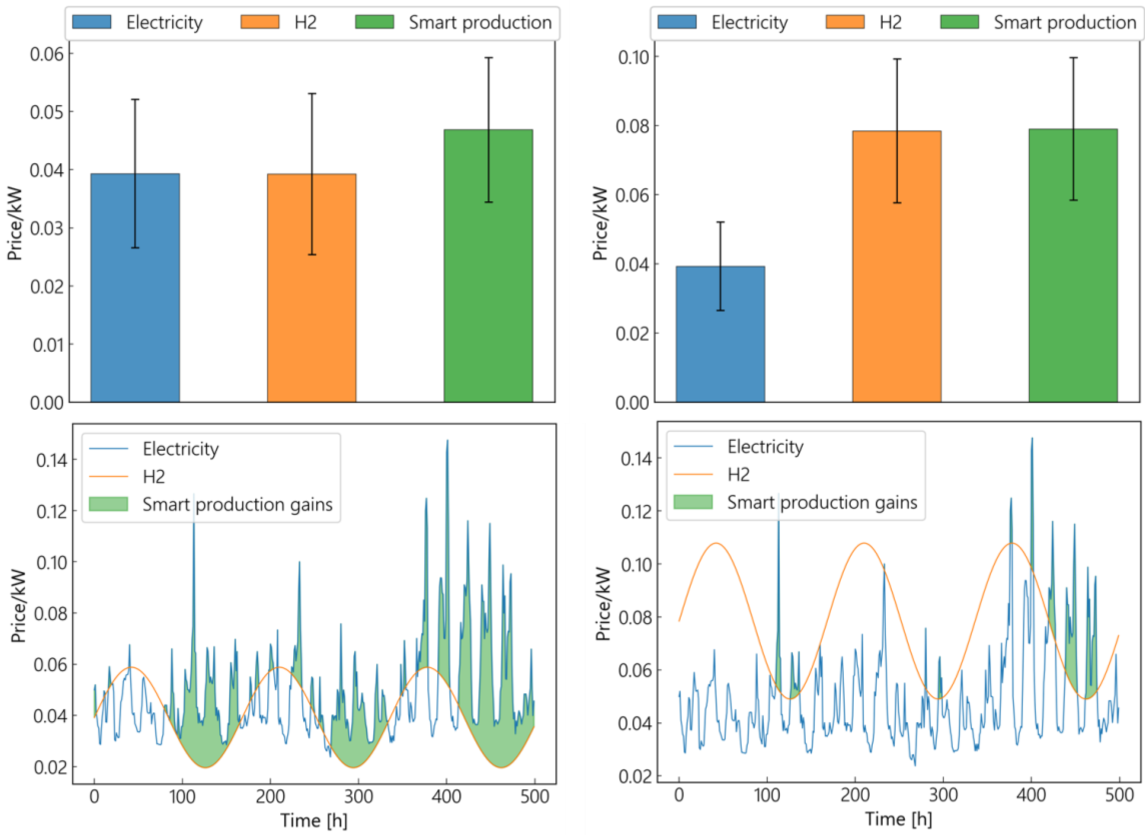


Figure 10: Effect of smart production in effective selling price for mean H2 price of 2.0 EUR/kg (left) and 4.0 EUR/kg (right).

The effect of the most profitable commodity per time step is also reflected in the optimum configurations found by the optimizer. Table 3 shows this effect. For the case of a mean H2 price of 2.9 EUR/kg, the optimum electrolyzer size almost doubled. With this specific set of boundary conditions, as seen in Figure 9, a larger electrolyzer can operate at higher efficiency levels for the same input power. Two columns are present in the profit gain. The first one refers to the baseline case of 425 MW. For the case of 2.0 EUR/kg, the baseline case configuration, operated in a smart production setting, was almost 4% more profitable than if always producing H2. For the optimum design, the largest gains were obtained for 2.9 EUR/kg. The cases of 2.0 and 4.0 EUR/kg had already very small and large capacities, respectively, and operating them differently did not result in significant profit gains.

Table 3: Profit gain via smart production for existing (baseline) and new optimum designs for multiple H2 prices.

	Optimum electrolyzer size [MW]		Profit gain via smart production [%]	
H2 mean price [EUR]	Produce H2	Smart production	Baseline design [%]	Optimum design [%]
2.0	50	50	3.8	0.4
2.9	425	800	1.3	2.3
4.0	800	800	0.1	0.2

3.4.3 Demand/pricing forecast accuracy: AI forecasting under uncertainties

To effectively perform smart production/operation, the accuracy of the demand and market prices needs to be sufficient. Figure 11 shows an example of ENTSO-E day-ahead load predictions. In the dataset analysed (years 2015-2021), the forecasting error (MAE) was around 10%. These errors are propagated to market models, as well as errors in supply predictions based on seasonality trends and weather forecasts. Due to the marginal characteristics of the electricity market, the propagation of these errors can result in very large deviations in pricing.

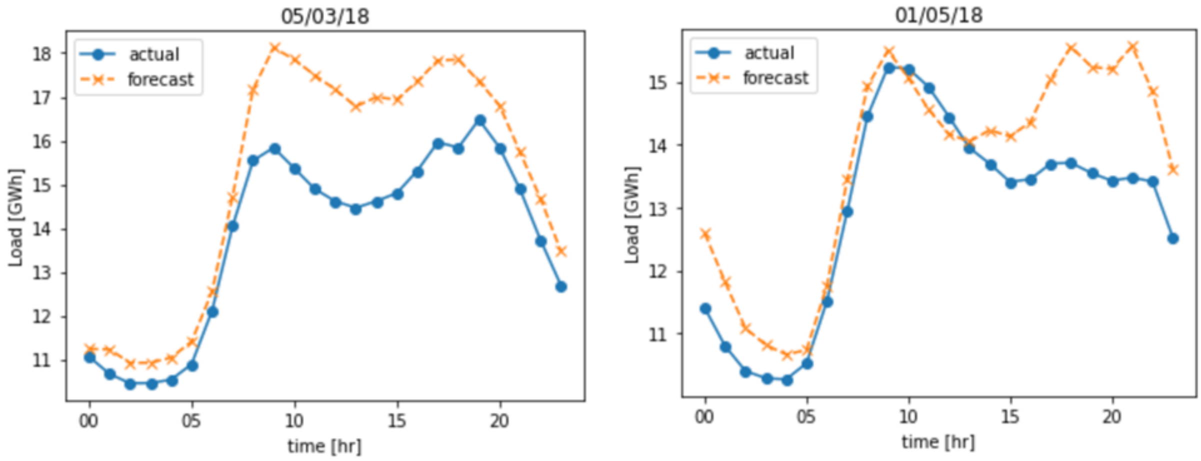


Figure 11: Examples of ENTSO-E day-ahead load predictions. Forecasting error is around 10% (RMSE=12%, MAE=10%) for the dataset analyzed (years 2015-2021).

A digital technology that can provide additional gains in this respect is AI forecasting under uncertainties. These are AI models that are able to predict point estimates of future supply/demand/energy prices *and uncertainty estimations* based on past trends, weather forecasts and also anomalies (e.g., extreme weather conditions, grid congestion in certain geographical areas, etc.). Figure 12 shows an example of a study by TNO in applying this technology to the electricity demand of the Netherlands. It can be observed that the MAE is around 2-2.3% in predictions for the next week and the next month.

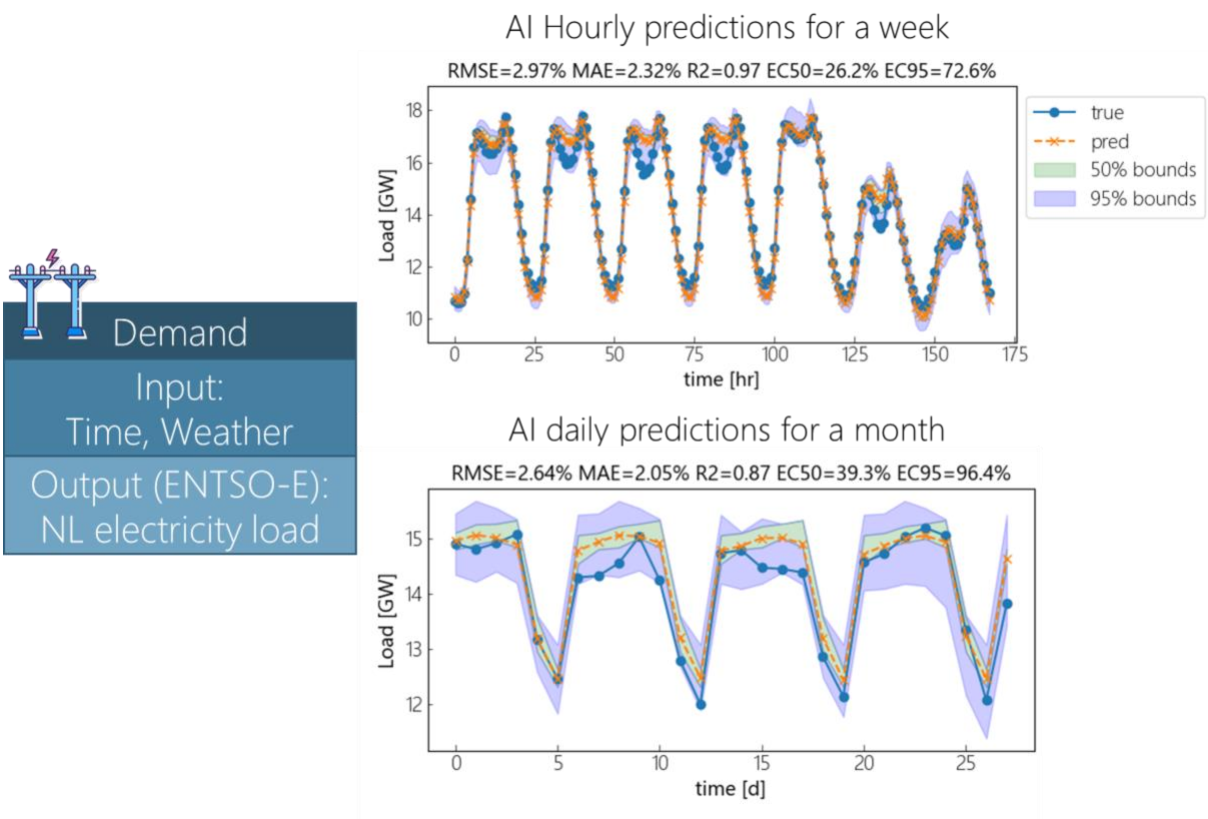


Figure 12: AI predictions of electricity demand of the Netherlands a week and a month ahead. MAE (proportional) and RMSE of less than 3% in both cases.

In addition, when using daily predictions, 96.4% of the points predicted are in the 95% predictive intervals. This means that the uncertainty estimates are well calibrated, not too narrow (less than 95% of the points) or too wide (closer to 100%). The AI uncertainty techniques provide *dynamic* estimates: that is, they can not only predict global uncertainties, but also *when* it is expected to have largest uncertainties. This can be relevant for cases such as the imbalance market or for weekly/seasonal balances, as a signal to have power/H2 storages ready if necessary for potential excesses/deficits of energy.

3.5 Conclusions and a potential digital twin roadmap

3.5.1 Conclusions of test cases

This section highlighted the use of multiple digital technologies in a simple example of a multi-commodity asset located in the North Sea. Three main technologies have been shown: physical modelling via a digital copy of an asset, smart production and operation, and forecasting under uncertainties. One of the simplest examples has been shown, to highlight that **even for a very small number of actors/components, digital technologies can provide significant benefits.** The main results from this study are:

- **Optimum design via physical modelling/digital copy:** accurate modelling of the physical components of the system can provide up to around 4% of profit gains in 2 of the 3 cases tested. The dynamic interactions between wind power and electrolyzer could be captured, allowing to understand if the asset components are operating at the expected efficiency levels. In a more complex case shown in the introduction of the digital copy, it was observed how static modelling might suggest an infeasible configuration in practice, and how dynamic modelling provides results that can vary up to 58% in their CAPEX.

- **Smart production and operation:** In this section, it was shown how significant improvements in the asset logic can be made via smart production and operation. In particular, it was shown how the effective mean selling price per kW of a commodity could be raised by 19% by the combination of physical modelling of the system with the smart operation. This could result in profit gains of up to 3.8% in the baseline configuration of H2 prices of 2.0 EUR/kg (existing asset) and up to 2.3% for 2.9 EUR/kg in the optimum configuration (optimum future asset). In other sets of boundary conditions, the differences were significantly smaller/negligible.
- **Forecasting of power and pricing via AI under uncertainties:** the importance of accurate and robust models to predict demand and pricing was shown, and its connection with smart production and operation. AI models to predict electricity demand and associated uncertainties were showing, decreasing the error from public forecast (ENTSO-E) from 10% to 2-2.3%. When using daily predictions for the following month, the model covered 96.4% of the points in the 95% predictive intervals, showing its robustness in multiple conditions.

3.5.2 Towards a digital twin roadmap and connections with other NSE WPs.

The effort to build a collection of digital twins for the future North Sea assets can start *now*. A possible roadmap to achieve it could be:

- **Phase I, North Sea Digital Model:** Construct connections between multiple assets and boundary conditions, combining physical modelling technologies such as PyDOLPHIN with AI technologies for forecasting, optimization and control (variational optimization, Reinforcement Learning). Validate these models and enhance them using lab-scale experiments and/or limited amount of field data. Data collaboration and sharing for joint profit gains.
  - *Non-real time, longer time scale problems*. Novel configurations and assets (1-year to 30-year time horizons). Optimum sizing, connections and geographical locations. Operational setpoints for weekly/seasonal balance. Optimum storage (electricity, H2, etc.) design and allocation. Test setpoints for current/future asset states.

- **Phase II, North Sea Digital Shadow:** Auto-update models using real-time data. Automatic setpoint generation via real-time optimization algorithms. Anomaly detection. Degradation calculations. Alert systems for operators.
  - *Real-time operator support:* real-time decision-making suggestions, for problems such as fast/slow-response component dynamics, hourly/daily balancing, the imbalance market. Automatic calibration and adapting signals when to perform maintenance or inspections.
  - The additions of sensors, big data, data sharing and cybersecurity technologies will provide additional accuracy and insights to the digital shadow.

- **Phase III, North Sea Digital Twin:** Full integration with the physical asset, acting as an EMS (Energy Management System), closely integrated with the hardware. Digital operation, with a human-in-the-loop for supervision. Automatic control and short/long-term real-time planning.
  - *Real-time digital operation*: AI operation for a wide range of time scales. Automatic market bidding depending on present/future conditions. Pre-emptively design logistic pathways for maintenance and support.
  - Development of data sharing technologies will be key to enable an optimum, fair and federated decision between different actors in the North Sea.

These three phases will be linked with three potential digital innovations for the North Sea in the next section.

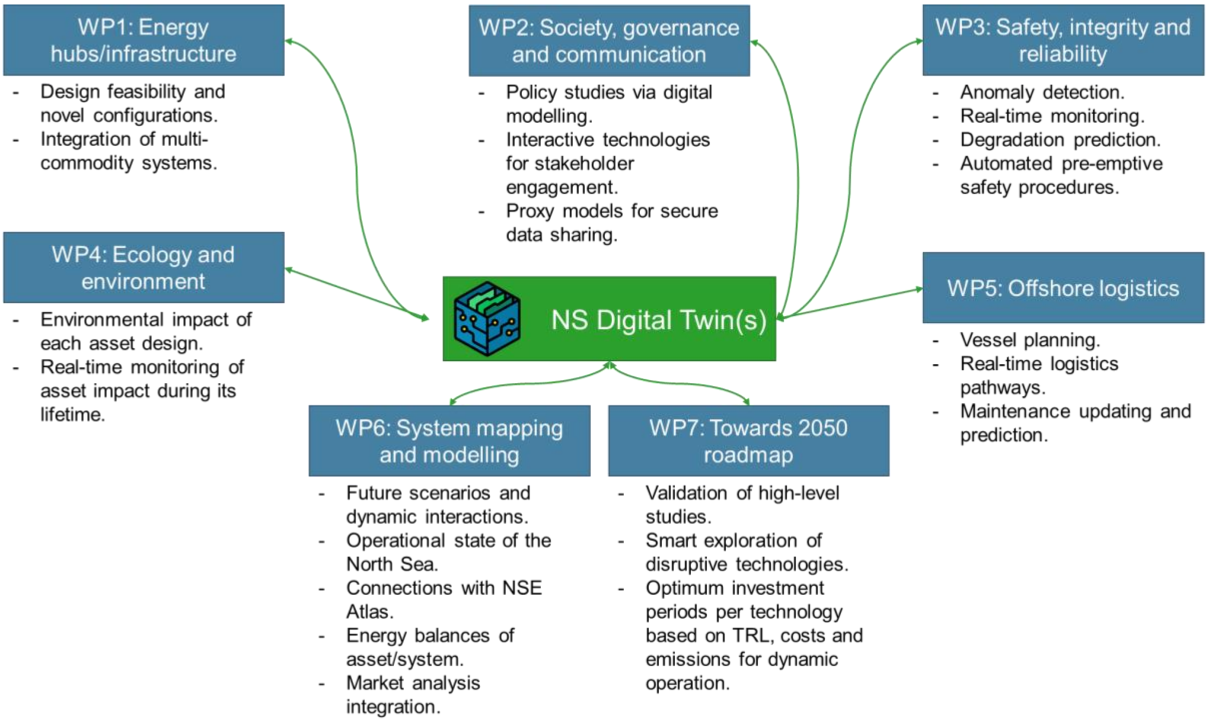


Figure 13: Connections of a North Sea Digital Twin with other NSE Work Packages.

Finally, Figure 13 shows the connections of a North Sea Digital Twin with other Work Packages of the North Sea Energy project. It can be observed that a Digital Twin could provide synergies with each of the WPs, as its nature goes from exploratory, long-term purposes to operational, short-term operation, maintenance, logistics, etc. As mentioned in Section 2, multiple digital twins are expected to be created and interconnected, tailoring them to each specific application.

The communication of these digital twins is expected to be developed via a standard language such as ESDL. A common communication language will allow to perform analyses with high-level system optimization tools (OPERA), network, multi-commodity systems (AURORA/Multi-Commodity Grid Simulator) and detailed physical, asset properties design and operational optimization (PyDOLPHIN). This will provide a rich ecosystem to future energy system operators, policymakers and other stakeholders.

4 Digital innovations for the North Sea

In this section, we consider three possible innovations based on combinations of the digital technologies reviewed above, to be deployed in the future North Sea Energy system. As summarized in Table 4, we proposed digital solutions for different goals and different time horizons.

Table 4 – Proposed innovations for the digitalization of the North Sea Energy system.

Goal	Challenges	Innovation	Technologies	Barriers	Horizon for technology readiness
Efficient design, production and operations	Dynamic supply/demand, component response, capacity, ramp-up time, fluctuating prices	Trusted digital twin	Digital twin, Sensors, Industrial IoT, Data Sharing, Cybersecurity	Integration, Data quality, Security	Short-term
Predictive maintenance	Asset/component degradation, Logistic planning of maintenance	Smart detection of anomalies and degradation	Big Data Analytics, Sensors, Industrial IoT, Data sharing	Integration, Data quality, Technology maturity	Medium-term
Autonomous inspection and repairs of offshore assets	Inspection, maintenance & repair in harsh weather conditions. Reduce emissions.	Autonomous vessels	Sensors, Robotics and automation	Technology maturity, Economical, Standards and regulations	Long-term

4.1 Trusted digital twin for efficient design, production and operation

Problem statement: Several challenges will be encountered when designing and operating future offshore energy systems. These includes the need to match highly dynamic supply and demand; to handle the different responses in the integrated system that will feature components with various capacity and associated ramp-up time; and to optimize production, conversion, storage, transport and export in a market with highly fluctuating energy prices. Not addressing these challenges might result in large profit losses, inability to guarantee security of supply, inefficient usage of the system (ranging from power curtailment due to unnecessary power production to dynamic bottlenecks along the asset line when operation conditions do not suit component responses), until faster component degradation and failure when operations are outside the safe regime.

Proposed solution: A trusted digital twin is the proposed digital innovation to achieve efficient and robust operations. Recent developments in such technology will allow to deploy this solution in the short-term. Already in the design phase of the future energy system of the North Sea employing a digital twin can be beneficial to identify a design that is robust to the future challenges. The digital twin will consist of physics-based (similar to what has been showcased in the previous section) and AI models, and it will leverage the (real-time) data acquired from sensors placed throughout the asset line and integrated via IoT platforms. It will be able to simulate both the dynamics of the system components and their interactions, and the variations in the boundary conditions (e.g. changing wind, fluctuating demand, forecasting market prices). It will feature control and optimization algorithms, and it will exploit the measured operating conditions and its capabilities to simulate what-if scenarios, to indicate optimal set-points and operational strategies. This technology can start in the design stage by creating virtual models of potential new systems. These virtual digital models will be based on data from historic/existing components and technology/market developments to define potential operational constraints, bottlenecks and optimizations. Once a configuration is built, this digital copy can develop into a digital twin. The challenge in the development phase of this innovation will be to demonstrate that the information from the digital twin can be trusted by the stakeholders and value chain. Models will be calibrated to obtain output with an accuracy sufficient for the desired operations. Possibly, the results should be made interpretable so that operators can better understand and trust the digital twin. The outcome of the digital twin should also be accompanied by the level of confidence/uncertainty on the prediction, such that tasks concerning risk-assessment can be made straightforward. Lastly, in case of data sharing between the partners the trusted digital twin should allow for a secure data or insight sharing between parties.

Furthermore, computational tasks need to be achieved within a certain time compatible with the requirements of operations, for example when real-time decisions are crucial. All these requirements might be sector-specific and therefore it will be necessary to develop common frameworks when looking at the North Sea Energy system. Understanding which sensor data can be used, how frequent and accurate the data needs to be, will be necessary steps to tailor the digital twin.

Potential barriers: Specific barriers to optimal deployment of the trusted digital twin are data availability, quality and physical/digital integration. Exploiting sensors and technological advancements in the Industrial Internet of Things will allow to acquire and make use of meaningful data in real-time. When considering a digital twin for the entire North Sea Energy system, it will be crucial to have a data sharing framework that will allow mutual gain from information sharing while maintaining privacy. Finally, the digital twin must be protected from outside threats, and cybersecurity technologies can overcome this barrier.

Expected benefits: Efficient and robust design and operations will guarantee security of supply, maximize profits and avoid unsafe operations, therefore preserving components integrity and extending system run lifetime. The trusted digital twin can be a driving force to accelerate system integration and collaboration within the North Sea.

4.2 Smart detection of anomalies and degradation

Problem statement: The detection of anomalies and degradation is a process that is usually performed reacting to the data available after inspections/sensor data show certain patterns. Typically, 20-25% of the LCOE for an offshore wind park goes to operations and maintenance. Harsh weather conditions accelerate component degradation and failures. Current rule-based or pure physics-based models can be either too inaccurate or computationally inefficient to predict these effects in real-time.

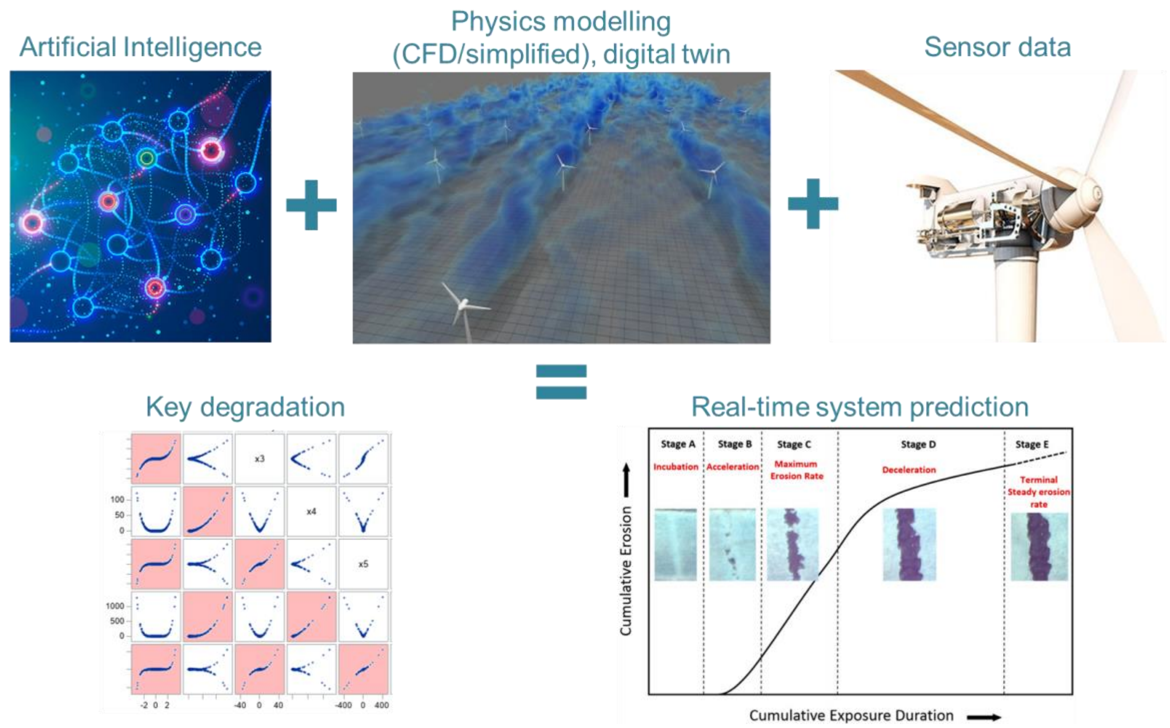


Figure 14: Schematic overview of a configuration for smart prediction of anomalies and degradation using digital technologies

Proposed solution: Figure 14 shows a schematic overview of the proposed digital innovation for a future North Sea that aims to shift from reactive to predictive maintenance. It consists in combining technologies such as Artificial Intelligence, high-fidelity/fast physics (such as CFD or other simplified approaches) and sensor, inspection data, key degradation parameters and an assessment of the system performance could be performed in (nearly) real time. A potential workflow of this system would be:

- **Sensor data, integrated in each wind turbine,** would be connected to a centralized location in the wind park (industrial IoT).
- Sensor data is sent to the **central processing system, where AI/data-driven algorithms** analyse if the data received (power produced with respect to setpoint and weather conditions) is potentially anomalous. The system raises a potential anomaly flag if needed (Big Data analytics).
- **A physics-based digital twin** (such as the one shown in the previous section) calculates the theoretical power output for different degradation scenarios. This data is compared with the sensor data obtained, and a real-time system prediction *of the degradation state and potential evolution* is given. This could serve to give key performance indicators such as degradation phase, remaining lifetime, etc.
- **If desired, this system could be coupled with an optimization/control algorithm** to change the operating setpoint to adapt to the degrading system.

  Additional considerations to this digital innovation are:
- The AI systems could be continuously updated based on the latest system data obtained.
- Several wind parks/operators could collaborate to the development of the AI algorithms, which would have a larger pool of data to be trained with (Secure Data Sharing).
- This system could be coupled with maintenance algorithms/route planning, for smart logistic maintenance, potentially encompassing several stakeholders to take advantage of synergies.

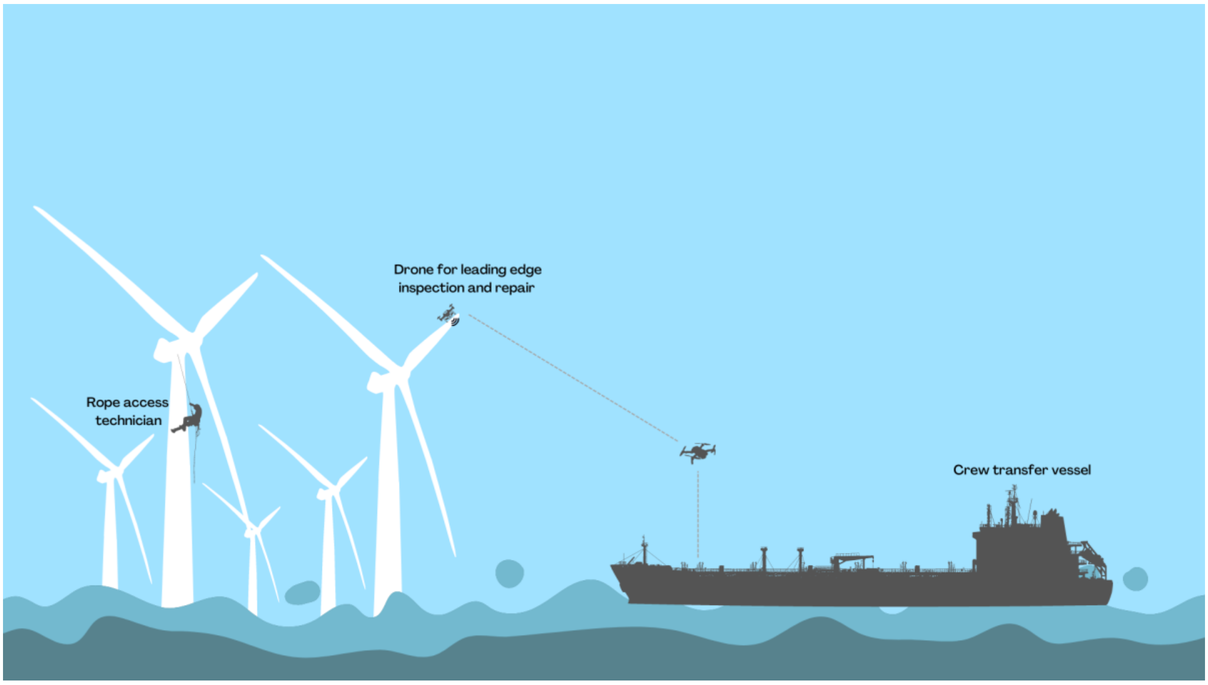
Potential barriers: Sensor placement difficulties (costs, location and maintenance) should be investigated. Data from sensors/inspections should be of sufficient quality to be used by AI algorithms. Research should be dedicated to identify the optimum sensor placements and minimum requirements on data (type, amount, frequency, accuracy) needed by a specific AI method for the predefined task.

Expected benefits: Reduction of downtimes via proactive maintenance. Better understanding on parameters that affect degradation/failure, which can lead to more fit-for-purpose designs (such as blade treatments). Data library to be used for future asset configurations (e.g., design wind farm taking into account previous degradation patterns). A better prediction of degradation and failure will also enable an improved planning of the O&M services and logistics.

4.3 Autonomous inspection and repairs

Problem statement: The anticipated expansion of offshore wind in the North Sea will present a number of difficulties, including the need for cost and emission reductions. Offshore wind turbine rotors are growing in size, which is causing the blade tip speeds and forces to rise. Damage to the blades result in decreased aerodynamic yield, increased load on the drive trains, and grid outages. Blade inspection is not only costly and risky, but also time-consuming, resulting in downtime, and it can only be done under specific circumstances (feasible weather, the presence of technicians, etc.).

One of the biggest problems for wind turbines in the offshore environment is leading edge erosion (LEE), which is a result of several meteorological conditions (water, salt, soil), as well as damage from precipitation (rain, hail). LEE poses serious operational, maintenance, and economic challenges.



Proposed solution: Drone-based automated sensor and coating systems are suggested as a way to improve inspection and repair procedures. The basic idea is:

- A drone platform equipped with a remote sensing sensor module can be used to find and assess the LEE of on-site rotor blades. A CTV (Crew Transfer Vehicle) is used to deploy the drone from a module close to an offshore wind turbine. In order to do remote sensing, the drone will hover in front of the turbine blades. It will then land on the leading edge (LE) of the blade, lock itself to the LE, and move along its length.

- An automated leading edge protection (LEP) solution for the repair of LEE will be deployed concurrently to solve blade erosion damage. The drone would have to come into touch with the blade for both the steps.

Potential barriers: Current drone designs and controls are not robust, stable and safe enough to operate in challenging offshore conditions. Further research and pilot projects in this regard would be useful to identify the limiting weather conditions for operations.

Expected benefits: A major part of the manual work for inspections may be done considerably more effectively and safely by autonomous drones for LEE and structural damage inspection, including for leading edge maintenance. Potential cost savings might be achieved through improved production efficiency and lower O&M expenses, which translates to an annual O&M cost and emission reduction.

5 Conclusions

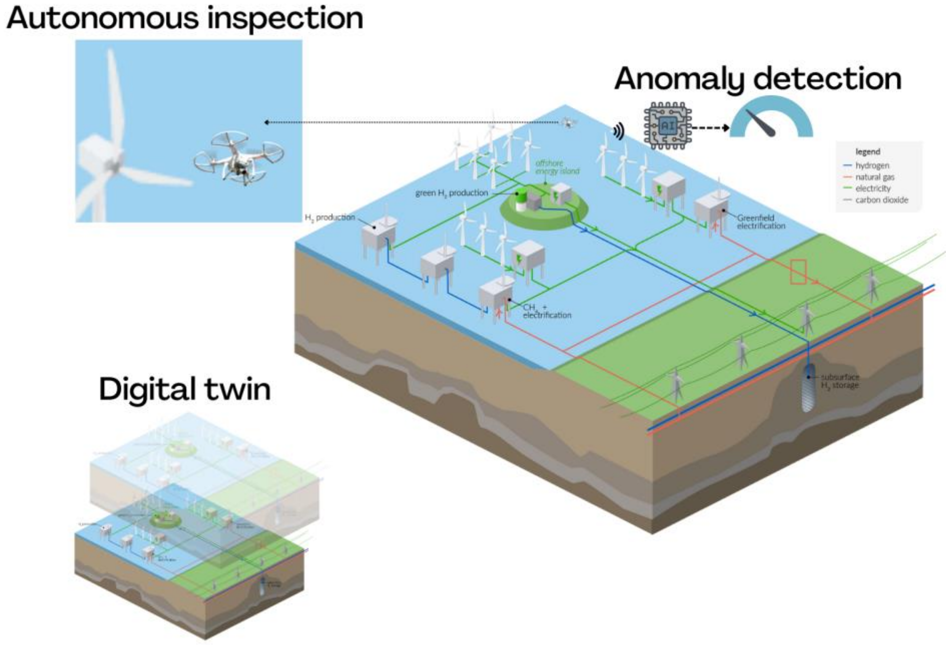


Figure 15 – Illustration of the future North Sea Energy system empowered with the three digital innovations proposed in this report. A digital twin will allow efficient operations, AI will be used for anomaly detection and predictive maintenance, inspections and repairs will be executed in an autonomous fashion.

In the first part of this report, nine major digital technologies (Digital twin, Big data analytics, Immersive technologies, Industrial Internet of Things, Robotics and automation, Sensors, Additive manufacturing, Cybersecurity, Data sharing) have been reviewed and their benefits in the context of offshore energy system have been highlighted. Potential digitalization barriers associated to economic aspects, system integration, data quality, security, technology maturity, standards and regulations, and job market have been described.

A case study with a simplified system, as a first step in the definition and application of a digital twin in the North Sea, has been presented. The use of three main technologies were described: digital copy via physical modelling, smart production/operation strategy, and AI forecasting under uncertainties. It was shown how these technologies can provide fit-for-purpose asset design and operations taking into account the physical components, supply/demand and market prices. These digital technologies will help to increase profits and the resilience of the system against highly dynamic, difficult-to-predict conditions. A roadmap of the different steps and potential applications of digital twins in the North Sea was shown, towards real-time integration and autonomous/operator-assisted operation.

A trusted digital twin will be of paramount importance to achieve efficient operations in the interdependent NSE system. This system will face several challenges both due to the variable dynamics of supply/demand and market conditions, and the complexity associated to system integration given the dynamic responses of the different components. Security of supply and profit maximization will be the reward in case of a successful digitalization process. In addition, proactive maintenance will be crucial to reduce downtimes and to avoid failures. Anomaly detection and predictive maintenance will be performed by centralized AI algorithms that can exploit sensor data and can be linked to digital twins to monitor in real-time malfunctioning and to forecast the degradation state of each component. The success of these innovations will depend upon further research on optimal sensor placing, on the identification of algorithm- and task-dependent requirements for data quality, and on data sharing protocols. In the deployment phase, attention should be paid to assess cybersecurity threats. Finally, in a farther future, inspections and repairs of critical components that must be performed in harsh weather conditions, such as for offshore wind turbines, will be executed in an autonomous fashion. The use of drones will allow safer, more effective and profitable solutions for maintenance. Such innovation will be boosted by additional research on control algorithms for drones and on digital solutions to exploit sensor data. Similar approach will be advantageous for decommissioning of existing infrastructure and for new installation.

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Appendix A
Digitalization workshop summary

In tandem with the activities of the NSE programme, a webinar/workshop was organized by TNO to present and discuss the challenges to be addressed in the future North Sea Energy area, and their vision on the main digital innovations that can help solve these challenges. The workshop combined the presentation of these challenges and innovations with a number of polls to get feedback and opinions from the audience, which consisted of a wide array of parties connected to larger NSE value chain (including asset/grid operators, service providers, and knowledge institutes both from within and outside of the NSE consortium).

The challenges that had been identified were divided into three topics corresponding to the different phases of the energy asset/system lifetime:

- Design challenges, including the future evolution of supply and demand, changes in subsidies, taxes and the cost of technologies, the phase out of old technologies and introduction of new ones, and the sizing and placement of energy system assets and equipment.
- Operation, maintenance, and services challenges, including the dynamic supply of future energy sources, fluctuating demand and energy prices, whether component can respond to such changes (including ramp-up time) and have the capacity to do so, how to anticipate and react to component degradation or failures, and the planning of maintenance logistics.
- Decommissioning challenges, including the estimation of asset end-of-life, the economic trade-offs between removal versus re-use, organizing the logistics of decommissioning, and reducing the impact on ecology and environment (through recycling of materials) of such activities.

During the workshop, three digital innovations were presented that could aid in solving some of these challenges. These three innovations were: digital twin technologies, AI and machine learning modelling, and data sharing. Through examples from other industries, and previous projects within TNO, these innovations were introduced and explained in more detail.

During the second half of the workshop, TNO's vision of a digital twin of the future that combined different aspects of the three innovations was presented. The digital twin would combine data sharing technologies such a secure multi-party computation and federated learning with AI modelling techniques such as explainable and transparent data-driven artificial neural networks and agent-based optimization with the goal of enabling parties in the NSE area to safely share data and leverage it to support the five sections of the NSE programme: design and integration, operation and maintenance, services and logistics, ecology and environment, and decommissioning and abandonment.

After the presentation, the audience was asked for their opinions on specific problems that could benefit from the presented innovations and digital twin concept, which were later assigned to the five aspects listed above. Based on this, it was found that for now challenges are mainly related to design, operation and maintenance, and logistics of the energy system, mainly due to the fact that these are the issues that are most practical and pressing at the current time (e.g. decommissioning is for most parties further away). Example problems include: logistic vessel planning, data availability, reliability and security, energy supply/demand as well as weather forecasting, and asset performance and maintenance planning.

After the discussion, the workshop was closed out with the presentation of a number of possible case studies that could be tackled with the present parties in future projects, including: a multi-party data

sharing and federated learning pilot for logistics planning, improved system and energy asset modelling using A/machine learning models, agent-based optimization of supply/demand management or system/asset design, application of explainable and transparent AI, and the development of models for designing, operating, and maintaining the future energy system.
Finally, the audience was again given the possibility to provide their own opinions, and were asked to list challenges they were currently facing or expected to face in the future that could potentially be solved through AI techniques. The answers were again grouped based on the five aspects of the NSE programme listed previously. These example challenges are listed below:

- Design and system integration: offshore grid design, design for decommissioning, defining/ determining facility availability, zero-emission natural gas production, optimization of meshed grids for power and hydrogen transport, minimizing maintenance or inspection requirements over the design life, optimum sizing and location of storage units (or other assets), using existing assets versus placing new ones (including re-use of pipelines for hydrogen or CO_2 transport).
- Operation, maintenance, services, and logistics: sharing logistics between wind and gas, frequency prediction for planned and unplanning maintenance, vessel and helicopter planning optimization, smart planning of maintenance engineers for different assets, autonomous inspection/maintenance vehicles, insurance of data quality and analysis of inspection data.
- Ecology and environment: understanding wildlife activity in planning new installations, risk of CO_2 leakage from abandoned wells being re-used for carbon storage.
- Decommissioning and abandonment: decommissioning planning across the interconnections of the bigger system, degradation predictions in combinations with maintenance and operational costs, well P&A project performance, and taking into account wildlife migrations in the planning of decommissioning.

Based on the outcomes of the initial workshop, a follow-up discussion was held for the same audience in which TNO presented three more detailed case studies that could be worked out in potential future follow-up projects:

- Supply-demand matching in an integrated North Sea Energy system, which focussed on initial activities for the development of a digital twin of the North Sea including data sharing, fast AI models, and dynamic optimization of supply and demand. This case study could possibly be integrated with the NSE Atlas, focussing on the Energy Hubs identified in the NSE programmes.
- Energy system design using AI. This case study was aimed more at the design of an integrated energy system, including the sizing and placing of assets under certain constraints and dealing with multiple objectives (reducing costs, minimizing negative ecological/environmental impact, and designing for re-use and decommissioning).
- Offshore logistics optimization. A case study aimed at optimizing offshore energy logistics and reducing costs and emission through the sharing of data between parties.

After the case studies were presented, the audience was given the chance to give their thoughts and opinions on them, and were asked to indicate their potential interest in the cases. From this it was found that interest lay mostly with the design and logistics cases, as they were at the current time the most relevant and addressed the most pressing challenges (supply-demand matching was as of yet less interesting as the system itself was not yet in place, so improving management of it was not yet as relevant as the other challenges).

In collaboration and appreciation to

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offshore system integration