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Digitalization Potentials in Supporting Offshore Wind Logistics

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Digitalization complementing offshore wind energy is a topic of interest for both researchers and practitioners. As part of a broader research on offshore wind logistics optimization, this paper focuses on how digitalization can be further developed to support logistics in the particular domain of offshore wind farm construction, as well as Operations and Maintenance (O&M). This paper analyzes five major digitalization potentials: the use of unmanned systems, 3D printing, motion sensors, big data techniques and LiDAR usage. The term Industrial Digitalization Technologies (IDT) summarizes these potentials. This contribution provides an initial mixed method analysis on enhanced offshore wind efficiency. Initial frameworks based on in-depth literature analysis on the one hand and on experimental break-even calculations on the other, are provided. This paper's outcome shows that unmanned systems provide the by far largest cost-saving potential.

Keywords: digitalization; offshore wind logistics; optimization; LCOE

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1 Introduction

Offshore wind is a promising renewable energy source. Its main challenge however is its profitability, which is a key driver for any industry especially in the energy sector. Logistics could represent a large share of offshore wind farms costs and be consequently an important contributor to improve profitability. Moreover, wind turbines are increasing in size and wind parks tend to be installed further away from coast in less favorable weather conditions, leading to more difficul vessel operations and higher risks. It seems then appropriate to find ways to improve logistics for better offshore wind profitability.

As described by Made Smarter (2017), different industrial revolutions had great influence on industries productivity and consequently on their profitability: first industrial revolution, originating from the textile industry, was driven by transition from manual production methods to manufacturing using machinery in the 18th century. Later on in early 20th century, mass production and Fordism brought the second industrial revolution. The third industrial revolution arose as computers were introduced in production process. With support of Internet, fourth industrial revolution is currently initiated and related to digitalization. In this last revolution, called as well Industry 4.0, technologies used are referred to as ”Industrial Digitalization Technologies” (IDTs).

Øydegard (2017) suggested future research on the digitalization of offshore wind that could be done within several areas and pointed out logistics as one of them. On the industrial side, MHI-Vestas (2018) indicated that digital transformation has started improving the capabilities to collect, sort and analyze data, and also combined it with machine learning and artificial intelligence. Siemens (2018) recently indicated that digital intelligence is a differentiating factor against its competitors, while E-ON (2018) is using data to increase the accuracy of actions. Furthermore, Statoil (2018) is investing to secure a global leadership position within digitalization.

As an interest from researcher and practitioners is identified, this paper intends to highlight and analyze potentials of digitalization processes that support offshore wind logistics leading to possible cost reduction.

This study addresses the following research questions:

Q1: Which IDTs could support offshore wind logistics in order to reduce costs?

Q2: How could such processes relevance be evaluated and compared?

Q3: What are the limitations of digitalization in offshore wind logistics industry?

2 Methodology

Research on innovative digitalization opportunities in the offshore wind industry is accompanied by a scarcity of existing literature and quantitative data. In order to cope with this aspect, this paper applies mixed method concepts of qualitative literature analysis, initial framework introduction and a case study of quantitative break even analysis to provide a valuable basis for future research on IDTs in the offshore wind sector.

Chapter three provides an in-depth qualitative literature analysis on the three main areas of Levelized Cost Of Energy (LCOE) definition, LCOE reduction potentials and IDT integration in the offshore wind industry. The literature review was conducted using Google Scholar between March and May 2017 focusing on a variety of key words such as ’LCOE reduction’, ’LCOE in offshore wind’, ’off-shore wind digitalization’, ’offshore wind innovations’ and ’offshore logistics digitalization’. Technical aspects were disregarded for the sake of this paper’s limitation to digitalization in the offshore sector. Furthermore, contributions and discussions among experts on the 6th International Conference on Dynamics in Logistics in February 2018 were taken into account for this paper’s literature review.

This analysis findings are processed and presented within conceptual frameworks (following the definitions of Miles and Hubermann, 1994 and Maxwell, 2013). Quantitative aspect of this paper is founded on a break-even scenario analysis of IDTs in chapter 4 which aims at ranking and discussing such approaches using limited but real-life data. Limitations of this paper’s research are pointed out in detail in chapter 5. Finally, in chapter 6, paper contributions and further research opportunities are presented and discussed.

3 Introduction of research areas

Limited numbers of studies have, so far, been conducted on digitalization in the offshore wind business. First contributions focused on big data integration to improve offshore wind farms' maintenance (see Viharos et al., 2013; Brinch, 2015; Nabati and Thoben, 2017) but these studies did not cover the logistics during construction of offshore wind farms. Øydegard (2017) already pointed out the necessity of additional research when investigating new digital technologies to improve logistics in the offshore wind industry. First business-related sources provide roadmaps for digitalization (Made Smarter, 2017) and cost-reduction potentials (WindEurope, 2017) while academic contributions in that area are scarce. In the following, this paper's focus areas are introduced and qualitatively evaluated.

3.1 LCOE

LCOE reflects the 'lifetime cost' of an energy source 'per unit of energy generated' (The Crown Estate, 2012). LCOE as a cost metric provides valuable insights, allowing normalizing costs into a consistent format over time and technologies (Rhodes et al. 2017). Using LCOE as profitability estimation for renewable energy sources is widely accepted among existing literature. However, LCOE evaluation on offshore wind energy is, as of now, quite limited (see Levitt et al. 2011; Ioannou et al. 2015; Duan 2017). Levitt et al. (2011) developed a pro-forma cash flow analysis for 35 offshore wind projects in Europe, China, and the United States, in planned or operation phases. Ioannou et al. (2015) expanded LCOE to account for stochastic inputs via Monte Carlo simulations. Furthermore, Duan (2017) introduced cost components for offshore wind energy and analyzed influencing factor for various markets. Due to the limitations of this paper, only locally installed offshore wind farms and their LCOE structures are evaluated. The area of floating wind farms is therefore not taken into consideration.

Calculating and combining LCOE among various energy sources is a challenging task as it is affected by various regional and external factors. Among these factors are political orientations (such as tax reduction or subsidies) or weather factors of the plant's region. Rhodes et al (2017) provides a more detailed view on LCOE dynamics. Table 1 gives a brief survey on different LCOE sources in order to identify a general ranking of offshore energy expenses compared to other energy sources.

Table 1: Median LCOE prices of common US energy sources

Range for total system levelized costs in $/MWh (2017)			
	Min	Median	Max
Dispatchable technologies			
Geothermal	42	45	50
Advanced combined cycle gas	44	49	77
Conventional combined cycle gas	45	50	79
Advanced combined cycle gas with CCS	67	75	85
Advanced combustion turbine	75	85	129
Advanced nuclear	90	93	98
Biomass	74	95	111
Conventional combustion turbine	87	99	145
Coal with 90% CCS	111	119	140
Coal with 30% CCS	117	130	191
Non-dispatchable technologies			
Wind, onshore	41	59	77
Hydroelectric	50	62	74
Solar photovoltaic	42	63	114
Wind, offshore	122	138	169
Solar thermal	145	165	188

CCS= Carbon capture and sequestration
Source: U.S. EIA (2018)

As LCOE calculations vary, the outcome among different studies also differs for each individual energy source. In order to avoid a locally biased European point of view concerning offshore digitalization effects on LCOE expenses, Table 2 compares various US sources with European values for the six largest conventional energy sources.

Table 2: Comparison of US and UK LCOE

System levelized costs in $/MWh (2017)			
	US EIA (2018)	Bifera (2017)	Siemens (2014)
	US Median I	US Median II	UK Median
Onshore Wind	59	64	71
Combined cycle gas	50	70	67
Utility scale solar PV	63	83	130
Coal	125	108	77
Nuclear	93	126	79
Offshore wind	138	141*	123

*Source: NREL (2018)

Bifera (2017) compared the five major US sources in his study while US EIA (2017) referred to the data provided in Table 1. Recent European LCOE values for conventional energy sources were not found during this paper's literature review. The values, provided by a study of Siemens (2014) reflect the linear median of outlook values between 2013 and 2025. The authors are aware of the limited accuracy of these values but decided to integrate them in this study because the intention to briefly compare LCOE values was met. Nevertheless, offshore wind industry is still under great pressure to reduce costs in order to improve competitiveness with other energy sources.

3.2 LCOE reduction potentials

In order to properly analyze digitalization potentials towards their reduction effects on LCOE, one must understand how the costs of an offshore wind park are allocated among the park's lifetime. Figure 1 is a key driver matrix concerning LCOE with regards to its cost factors. Digitalization in offshore wind construction mainly affects capital expenses (CAPEX) in the beginning while digitalization in operations further affects long-term operation expenses (OPEX). Turbine expenses regarding CAPEX can be reduced using IDT in the construction process. A long term integration of IDT in the wind farm operation further enhances the farm's productivity, therefore positively affecting LCOE. On the OPEX side, regular maintenance is a key aspect of wind farm operations. Transformers, switches, breakers,

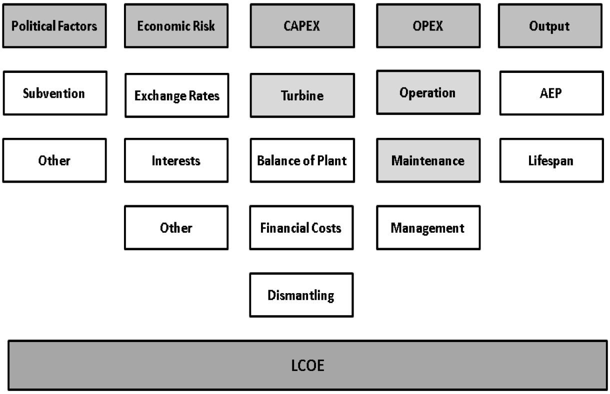

Figure 1: Key LCOE Driver Matrix

Source: Adapted from Lüthi and Prässler (2011), Prässler and Schaechtele (2012), Duan (2017)

relays, etc. are subject to regulatory protocols that determine the schedule for inspection ensuring safety to both farm and the personnel (Dovorak 2016). Using IDT in operations might also positively affect LCOE outcome by gathering and applying larger scales of data for optimization purposes.

The aspect of LCOE drivers becomes more complex as offshore wind farms themselves evolve and do not follow the same universal calculation patterns. As turbines increase in size and wind farms get installed further away from shore in harsher weather conditions, it becomes more and more difficult to operate vessels and, consequently, accessibility of offshore wind farms can be considered a major factor that escalates expenses and risks of offshore wind projects. These cost-increasing aspects were already identified by Van der Zwaan et al. (2012).

Tables 1 and 2 show the still high energy costs of offshore wind compared to other energy sources. At the same time cost-saving opportunities in offshore wind are presented throughout the literature. Offshore wind development will also benefit from cost reductions due to technological developments as well as learning and scaling effects (Van de Zwaan et al., 2012 and Chartron and Haasis 2018).

While the above mentioned sources remain rather general in their expression, recent contributions provide a more detailed view on the cost distribution and their cost reduction potential. Bloomberg (2017) predicted a reduction of offshore wind expenses by 71% by 2040 due to competition, experience and economies of scale. These predictions were complemented by Hobohm et al. (2015) indicating a 68% reduction of costs from 2010-2020 among German offshore wind farms. According to Hobohm et al. (2015), external factors would reduce offshore expenses by 13%. Technological developments would account for 38% whereas 30% can be attributed to more modern and larger turbine sizes. Excellence and maturation in processes finally account for another 40% of cost reduction that sums up to an overall reduction of 68% from base- to future case scenarios. It is worth mentioning that OPEX reductions only account for 5% while logistics improvements are not separately mentioned. According to other contributions, off-shore wind farm logistics costs range from 15% (Windenergy, 2009) to 19% (Ahn et al., 2016). Poulsen and Bay Hasager (2016) even provided a more detailed evaluation, in which logistics represents 18% of LCOE.

4 IDTs applicable to offshore wind logistics

In order to answer research question [Q1], the following chapter introduces and evaluates five major IDTs for the offshore wind logistics industry as a means of reducing LCOE. Assumptions used for break-even calculations (see chapters 4.1, 4.2, 4.3 and 4.4) are listed in Table 2. Estimated values from different sources or authors assumptions have been indicated in order to compare quantitatively presented IDTs (see chapter 4.6).

Table 3: Assumptions for break-even analysis

Symbol	Assumptions	Estimated Value used	Source
Bunk Cost	MGO bunker cost	0.45 € / liter	Ship & Bunker (2018)
CTV Max	Crew Transfer Vessel (CTV) consumption at maximum speed	500 liters / hour	Opus Marine (2018)
CTV Rate	CTV day rate	3,500€	Based on Phillips, et al. (2015), average for CTV with availability over 50%
CTV Red	CTV consumption at reduced speed 20 knots	380 liters / hour	Opus Marine (2018)
CTV Serv	CTV consumption at service speed	400 liters / hour	Opus Marine (2018)
D	Distance to shore in nautical miles	40	
Day	Ratio of day when a technician works less than 12 hours per day	65%	BMO offshore (2016)
less12h	Ratio of day when a technician works less than 12 hours per day		
H	Vessel net working hours per day	5	
IV Rate	Installation vessel day rate	220,000€	Based on Dalgic, et al. (2013), average spot market rate
Improv Dep CTV	Improvement in CTV deployment	25%	BMO offshore (2016)

Continued on next page

Table 3 – continued from previous page

Bunk Cost	MGO bunker cost	0.45 € / liter	Ship & Bunker (2018)
M	Marginal weather window	30%	BMO offshore (2016)
N	Number of vessel hire days	Variable	
nI	Number of interventions to bring a component from deck to nacelle on installation vessel	1 per vessel hire day	
nT	Number of trips to transport a spare part from onshore to offshore	1 per vessel hire day	
Speed Serv	CTV service speed in knots	26.5	Opus Marine (2018)
T Climb	Duration in minutes to climb from installation vessel deck to nacelle	20’	
T Lift Prep	Duration in minutes to prepare liftin equipment on the installation vessel crane hook	20’	

4.1 Motion sensors

Øydegard (2017) argued that an increased implementation of sensors on the support vessels would result in a higher level of autonomy to improve workability, availability of turbines and fuel saving. Offshore wave conditions generally result in a ‘grey’ area in the operating window between 1.2m and 2m of significant wave heights for Crew Transfer Vessels (CTV). According to BMO offshore (2016), the probability of that marginal weather window occurring is estimated at 30%.

External vessels are hired to perform in this marginal operating window, but lack of vessel performance data for marine control results in a best practice ’no-go’ decision at significant wave heights above 1.2m. It is estimated to realize a 25% improvement in deployment in this weather window.

Moreover, BMO offshore (2016) indicates that vessels are often sailing at full-speed to maximize technicians’ work time. It is estimated that in 65% of days, technicians are returning to port having worked less than 12 hours. Those instances allow reducing vessel speeds from 25/26 knots to 20 knots. The resulting fuel consumption can only be saved on the inbound and return legs; not on the outbound leg. Hence, a display indicating to the crew when to reduce speed, may reduce fuel costs.

Cost savings associated with implementation of such sensors could be evaluated by calculating the vessel’s additional active operation time due to more accurate evaluation of wave height marginal weather windows (”CTV Rate x M x Improv Dep CTV ”) and fuel saving due to an optimization of vessel speed according to technicians working time (”H x (CTV Max - CTV Red)x Bunk Cost x Day less 12h /2”). These savings are factored by the number of vessel hiring days (N).

BE sensor cost for such sensor can then be broken even as follow

$$\begin{aligned} BE\,Sensor = N \times (CTV\ Rate \times M \times Improv\,Dep\,CTV + H \\ \times (CTV\ Max - CTV\ Red) \times Bunk\,Cost \\ \times Day\,less\,12h/2) \end{aligned} \tag{1}$$

4.2 3-D Printing

3-D printing as a newly available technology in different industries and has so far not been introduced in the offshore wind sector. This promising technology could reduce storage efforts and avoid unnecessary cargo transfer of small parts. 3D printing in offshore areas was highlighted by Øydegard (2017) to ideally have components 3-D manufactured instead of having high-volume storage. A qualitative assessment on sustainability by Gebler et al. (2014) quantified changes in life-cycle costs, energy and emissions. Mohr and Kahn (2015) already identified seven key areas of logistics that will be affected by 3D printing technologies in the near future.

Cost savings associated with implementation of 3-D Printing could be evaluated by calculating the vessel charter rate *(D/Speed Serv x CTV Rate /24)* and bunker *(CTV Serv x Bunk Cost x D/SpeedServ)* savings. These savings are factored by the number of events (nT) and a factor 2 due to return trips.

BE 3D cost for 3D printer (installed onboard a ship or a platform) can be amortized as follows:

$$BE\,3D = (D/Speed\,Serv \times CTV\ Rate/24 + CTV\ Serv \times \\ Bunk\,Cost \times D/Speed\,Serv) \times 2 \times nT \quad (2)$$

4.3 Unmanned Systems (US) for access and inspection

Made Smarter (2017) foresaw benefits of using specialized robotics for maintenance on wind turbine blades as example as they are difficult to access. Øydegard (2017) evaluated autonomous vessels and drones for access and inspection as well. Stein (2018 I) analyzed the approach of using Unmanned Systems (US) for inspection works in the maritime domain. He argues that this innovation reduces costs and improves operations efficiency and safety. Another contribution by Stein (2018 II) further integrated the use of US in maritime and port security operations.

Inspection that would avoid transfer of personnel on the wind turbine, hence avoiding traditional transfer by CTV or helicopter, would reduce cost significantly. The same accounts for transfer of small spare parts or tools from the installation vessel deck to turbine nacelles. There are instances in which a missing tool or spare part during installation slows down operations. In order to bring a spare part or a tool to the top of a turbine, a technician needs to climb from installation vessel deck to nacelle which takes around 20 minutes in an elevator or a minimum of 30 minutes climbing. US can conduct such operations within few minutes.

Cost savings associated with implementation of US could be evaluated by calculating the vessel charter rate *(D/Speed Serv x CTV Rate /24)* and bunker *(CTV Serv x Bunk Cost x D/SpeedServ)* savings. These savings are factored by the number of events (nT) and a factor 2 due to return trips. Savings on Installation vessel due to reduced downtimes on installation critical path *(T Climb x IV Rate/24)*, factored by number of events (nl), are also considered.

BE US cost for US can be broken even as follows:

$$\begin{multline} BE\,US = (D/Speed\,Serv \times CTV\ Rate/24 + CTV\ Serv \\ \times Bunk\,Cost \times D/Speed\,Serv) \times 2 \times nT + T\,Climb \times IV\ Rate/24 \times nl \tag{3} \end{multline}$$

4.4 LiDAR

LiDAR (Light Detection And Ranging) is a surveying method that measures distance to a target using lasers. It can be used to accurately measure wind speeds and wind turbulences (Hasager, et al., 2007). For instance, there is potential application during wind turbine installation phase: before lifting components, it is necessary to accurately check actual wind speed at a certain height to prevent exceeding Marine Warranty Surveyor (MWS) or vessel capability limits. For such verification, installation vessels usually use anemometer on their cranes to decide whether or not to proceed. Hence, instead of preparing and attaching the component to be lifted to the crane, the crane is up in the air, determining wind speeds. The installation vessel is then systematically losing a conservatively estimated 20 minutes. Installing a LiDAR on the other hand could prevent this crane operation by providing an accurate wind situation at the component height lift level.

Cost savings associated with implementation of LiDAR could be evaluated by calculating savings on installation vessel hire due to reduced time of lift preparation *(T lift prep)*, factored by probability of such situation (M) and number of vessel hire days (N).

BE LiDAR cost for LiDAR can be broken even as follow

$$BE\,LiDAR = T\,lift\,prep \times M \times N \times IV \times Rate/24 \tag{4}$$

4.5 Big Data and Digitally-based Decisions

Use of data sources collected by proper instruments and analyzed using software embedded mathematical models already allows for a logical cost-effective decision-making process in the maritime domain. Jahn and Scheidweiler (2018) have developed an algorithm that analyzes ship movements from AIS and environmental data to calculate the ships' estimated time on arrival for optimized port calls. According to Vestas (2018) data about wind, weather and the real-time performance of almost 25,000 turbines worldwide, is currently being gathered and evaluated. Vestas considers that digitalization will help to get more precise weather forecasting. This aspect was highlighted by IRENA (2016) where improvement in weather forecasting and analysis is one of the main opportunities for O&M offshore wind cost reductions before 2025. Villani (2018) encourages research collaboration projects on weather forecasts and artificial intelligence in terms of risk assessments. Digitalization and big data analysis can help to monitor critical key performance indicators as well. Chartron and Haasis (2018) proposed a tool to collect relevant information to identify logistics inefficiencies during offshore wind park constructions and analyzed these inefficiencies to point out improvement opportunities.

In order to better plan offshore logistics activities, several researches have been conducted and constitute a blueprint for big data and real time decision making analysis: during the installation phase, several decision support and simulation tools have been developed (see Scholz-Reiter et al., 2010; Lange et al., 2012; Ritter, 2016; Vis and Ursavas, 2016). Further studies have been conducted to optimize vessel fleet during O&M phase (see Endrerud, et al. 2014; Dewan, A. 2014; Stalhane, et al. 2016) and additionally, on big data to improve offshore wind farms maintenance (see Viharos et al., 2013; Nabati and Thoben, 2017).

As big data is certainly a benefit for offshore logistics operations, it is complex to evaluate. Both economically a prospectively positive impacts cannot be evaluated without proper data so that no break-even analysis can be proposed on this specific aspect. According to the author's opinion, this topic is even without break-even information worth mentioning, as it already points towards future research on offshore wind digitalization.

4.6 Break even analysis comparison

In order to answer to research question [Q2], it is proposed in this sub-chapter to evaluate and compare selected IDTs.

The number of Vessel hire days (N) has been considered a common variable for the previously presented 4 IDTs, and break-even savings have been evaluated over one year (365 days) of operation. Using functions (1), (2), (3) and (4) and implementing estimated values from Table 2, we obtain results presented in Figure 2.

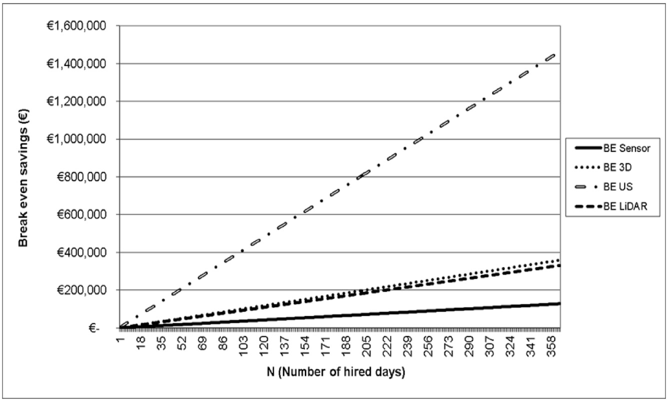

Figure 2: Break-even savings comparison between four different IDTs in offshore wind logistics

Figure 3 shows US IDT with the highest positive slope, reflecting the highest saving potential. This can be attributed to the fact that it can both save time on installation vessel as well as prevent travels of support vessels. With increasing payloads of US, the operability for spare part movement also increases. Nowadays a liftin capacity up to 5 kg is common around industrial US and this is likely to increase. Some limitations to consider may be authorizations to use US off-shore and having qualified personnel to pilot such systems.

3D printing IDT has the second highest saving potential. This IDT would be also particularly relevant in O&M phase were spare parts are sometimes needed urgently. Some limitations to consider may be the type of parts that can be produced, quality requirements, duration to create the part and skill to create the part offshore. Furthermore patent rights on specific parts or aspects might affect certain 3D printing procedures on specific parts.

LiDAR is the third highest saving potential IDT. It is applicable to installation vessel and would make sense on an installation campaign that requires the installation of several turbines. Some limitations to consider may be the reluctance of the offshore wind industry to use such alternative systems and having the necessary skilled personnel to use this new technology.

The last and in comparison lowest potential is coming from sensors IDT. This technology is applicable in the particular domain of CTVs. It can represent a high potential in O&M phase where this kind of vessels are used during several year periods. Some limitations to consider may be the cost of the technology and capability to analyze the data accurately.

Based on the above, Table 4 presents an evaluation of the potential impact on LCOE and investment for each IDT.

Table 4: IDT evaluation LCOE impact and investment

IDT	LCOE impact (Construction)	LCOE impact (O&M)	Investment
Unmanned systems	High	High	High- Medium
Big Data	Medium	High	Medium
3D printing	Medium	Medium	High
LiDAR	Low	Medium	Medium

4.7 Research barriers

In order to study research question [Q3], limitations on LCOE reductions via IDTs are evaluated in this chapter.

Since offshore wind projects are tending to be installed beyond the range limit of mobile phones and Wifi, connectivity is one of the key challenges. Splitting bandwidth and allocating it to specific tasks can be a solution to share limited connection capabilities.

Today, most of the vessel's information is coming from reports written by onboard employees. As technologies allow for better understanding of the vessel's activity (i.e. data coming from motion sensors and cameras) the amount of data to be processed increases. Figure 3 displays an infrastructure proposal of the integration of current offshore data into the communication architecture. Such cloud-based scheme, using multiple data inputs aggregated in databases, however, requires advanced modes on data processing and storage.

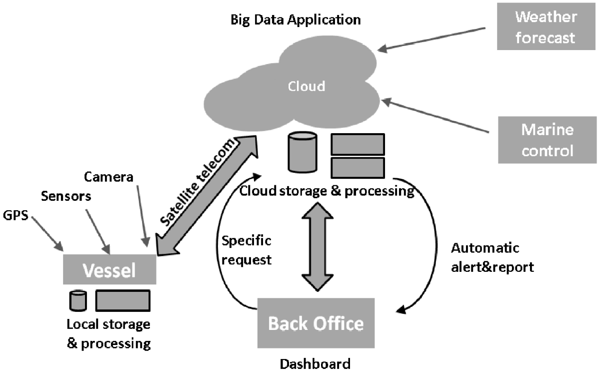

Figure 3: Architecture data processing and communication architecture

As high quantities of data are collected by physical sensors, on-board cameras, and human activity, concepts of edge-computing (see Carlini, 2016) are required to cope with current bandwidth limitations in remote offshore areas. Data management in remote offshore areas remains a considerable threshold to industrial digitalization technologies that requires additional research.

Made Smarter (2017) saw a need to adapt some digital technologies from more advanced sectors (nuclear or aerospace) to the offshore wind industry. Made Smarter (2017) further recommended more comprehensive and shared storage of geological or environmental data to reduce risks in the offshore wind industry. A2SEA (2018) for example implemented a turbine database in order to collect information such as vessels used, cables routes or seabed investigations. However, such databases are still rare in the offshore wind industry and not publically shared.

4.8 Discussion and conclusion

Even though it appears to be obvious that the fourth industrial revolution is now on its way and will hit the offshore wind industry sooner or later, several precautions need to be considered.

For instance, marine coordinators are key for offshore logistics' smooth operations and cannot currently be replaced by computers or advanced artificial intelligence since a lot of events are not predictable and communication or authorizations are still conducted manually. Moreover, according to Made Smarter (2017), offshore wind industry is still in an early development phase with a need to improve in integration and standardization. It was also highlighted by Chartron and Haasis (2018) that productivity techniques still need to be implemented offshore. In that case, it seems to be relevant to explore improvements brought by the third industrial revolution. A number of barriers and limitations need to be overcome, and before the fourth revolution receives the total focus of attention, offshore wind industry needs to properly complete its third industrial revolution.

Nevertheless; it is observed that the wind industry actors try to instill digitalization as a new topic to better serve customers and their specific markets. This contribution provides an initial mixed method analysis on enhanced offshore wind efficiency expressed by LCOE reductions through the use of IDT. Five IDTs have been identified as potential support for offshore wind logistics (research question [Q1]). Experimental break-even calculations have been proposed in order to answer research question [Q2]. Unmanned systems provide by far largest cost-saving potential regarding offshore wind LCOE. Concerning research question [Q3], limitations identified for IDTs in offshore wind context are connectivity, data management and cross-sector cooperation. Therefore, further research on improved information sharing or collaboration tools to support real time decision-making would be beneficial. Furthermore, this academic field would benefit from applied quantitative analysis and economic benefit investigations.

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