Using Big Data analysis to model vessel demand

The case of Crew Transfer Vessel demand for crew transfer operations in the offshore wind industry

R.G. Naeff

Thesis for the degree of MSc in Marine Technology in the specialisation of Shipping Management

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By

R.G. Naeff

Performed at

Damen Shipyards & Made Smart Group

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Company Supervisors

Daily Supervisor 1:	*ir. Y.P. van Vlimmeren*	
Daily Supervisor 2:	*E.J. Jeeninga*	

Thesis Exam Committee

Chairman:	*Prof. dr. E.M. van de Voorde*	*TU Delft*
Thesis committee:	*ir. J.W. Frouws*	*TU Delft*
	dr. ir. H.P.M. Veeke	*TU Delft*
	ir. Y.P. van Vlimmeren	*Damen Shipyards*
	E.J. Jeeninga	*Made Smart Group*

Author Details

Student number: *4050681*

Abstract

Problem statement - Damen Shipyards (Damen) wants to use Big Data analysis to gain new market insights and forecast vessel demand. These insights are valuable because Damen keeps standardised vessels in stock in order to significantly reduce delivery times. This concept gives Damen a competitive advantage, but is not without risk since they must speculatively build vessels beforehand. As a case, Damen wants to improve the current forecasting methods for the thriving offshore wind market - for which they supply vessels - based on data derived from the Automatic Identification System (AIS). AIS data includes among others information about identification, location, speed, date and time of approximately 200.000 vessels worldwide. Made Smart Group (MSG) is an information service provider specialised in nautical information, and maintains the world's largest AIS database. MSG and Damen joined forces for this research.

Objective - The objective of this research is to determine if and how Big Data analysis can be used to model (future) demand for Crew Transfer Vessels (CTV) being used for Crew Transfer Operations (CTO) in the offshore wind industry.

Methodology - Almost 45 million AIS location reports of 39 CTVs servicing 263 turbines in 3 offshore wind farms throughout 2016 are analysed to derive key figures of the executed CTOs. Key figures are e.g. the weather window, and the number of executed CTOs per hour. The CTV demand is modelled based on these key figures, and three wind farm specific input parameters: number of turbines, distance between wind farm and port, and the sea state distribution.

Results - The CTO demand of the 263 analysed wind turbines was on average 113 per year in 2016. This average CTO demand has a variation of almost 50% between turbine types. With an accuracy of 4%, it is modelled that a yearly average of 12.4 CTVs are needed to service these 263 turbines. Furthermore, the CTV demand decreases on average with 11% in the three analysed wind farms if the CTO limit can be increased from 1.5 m to 2.0 m mean significant wave height. This result in a potential cost saving around € 5.1 million on a yearly basis for these three wind farms alone.

Implications - AIS data can be used to model vessel demand and gain insight into the market size. The accuracy of the developed model can be improved by adding: more wind farm specific variables; and/ or data of more CTVs/ wind farms. The gained knowledge about using Big Data analysis to forecast the CTV market size is useful and important for the introduction and future development of commercial AIS based data analysis. Furthermore, it provides insights into the operational profile of CTVs. This can be used to develop better vessels, better service the market and ultimately help to lower the cost price of offshore wind energy. It is believed that the maritime sector could profit from AIS data analysis.

Preface

This master thesis is written to obtain the degree of MSc in Marine Technology in the specialisation of Shipping Management at the faculty of Mechanical, Maritime and Materials Engineering of Delft University of Technology in the Netherlands.

In a nutshell, my thesis is about processing location data of a large number of vessels to gain insights into vessel demand and its operational profile. This was my first, and probably not last, Big Data driven project. Now the project is finished, I am very glad that I challenged myself to learn about programming and managing data driven projects as I think these are very useful skills in modern business society.

I would like to express my gratitude to all who supported me during the writing of my thesis. I have learned a lot about structuring Big Data projects, AIS, critical and effective writing, etc. over the past 10 months, and I am very well aware that I could not have achieved this without help from others.

The Wednesday sessions at the TU Delft with prof. dr. Eddy van de Voorde and ir. Koos Frouws were something to look forward to. I enjoyed the discussions we had, and their feedback was always spot on and helped me to improve my work. I found it very special that these two knowledgeable and experienced men took the time to review my work and help me though the process.

I want to thank drs. Luuth van der Scheer and Bert Jeeninga from Made Smart Group for their time and effort they put into my work. Luuth and Bert helped me among others with the data processing part of my thesis and gave me practical and useful feedback throughout the process. Furthermore, they challenged me to think about how to deal with the different objectives from the university, Damen and their own company. It has been an inspiring experience to work with these two entrepreneurs.

A special thanks to ir. Yoush van Vlimmeren, my daily supervisor at Damen. As my first point of contact, Yoush helped me to structure the project at the beginning and provided critical feedback throughout the process that helped me to improve my work. Furthermore, Yoush always took the time to discuss the work whenever I needed to structure my thoughts or could use a new perspective. Of course, I will not end this preface without thanking the entire Business Development & Marketing Intelligence Department of Damen for letting me be a part of their team.

Finally, I want to thank my family, friends and of course my lovely girlfriend for supporting me throughout the process. It has been a memorable period.

Rens Gijsbrand Naeff
Delft, December 2017

List of Abbreviations

AIS	-	Automatic Identification System
C.C.	-	Correctly Counted Transfers
CAPEX	-	Capital Expenditure
CDF	-	Cumulative Distribution Function
CRISP-DM	-	Cross-Industry Standard Process for Data Mining
CTO	-	Crew Transfer Operation
CTV	-	Crew Transfer Vessel
Damen	-	Damen Shipyards
DBSCAN	-	Density-Based Spatial Clustering of Applications with Noise
ECMWF	-	European Centre for Medium-Range Weather Forecasts
FCS	-	Fast Crew Supplier
GPS	-	Global Positioning System
GW	-	Gigawatt
Hs	-	Mean significant wave height
IMO	-	International Maritime Organization
km	-	Kilometer
KP	-	Key Parameter
KPI	-	Key Performance Indicator
kts	-	Knots
LCOE	-	Levelised Cost of Energy
m	-	Meter
MMSI	-	Maritime Mobile Service Identity
MSG	-	Made Smart Group
MW	-	Megawatt
NPV	-	Net Present Value
nm	-	Nautical mile
NOAA	-	National Oceanic and Atmospheric Administration
O&M	-	Operation and Maintenance
OPEX	-	Operational Expenditure
RIB	-	Rigid Inflatable Boat
SOG	-	Speed over Ground
SOV	-	Service Operations Vessel
SWATH	-	Small Waterplane Area Twin Hull
t	-	Ton
TB	-	Terabyte
UTC	-	Coordinated Universal Time

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1 Introduction

This chapter introduces the subject of this thesis, the problem statement and relevant background information is presented to clarify the context and relevance of this project. Furthermore, the objective, research questions, scope and methodology are described, to finish with the thesis outline.

1.1 Big Data Analysis & Modern Business

Big Data has become an indispensable part of modern business environment, and large information tech companies such as Google and Amazon are forerunners when it comes to implementing Big Data into their daily business operations (Vahn, 2014; Vera-Baquero, et al., 2015). It is widely believed among business people that Big Data analysis has a positive influence on business performance, as it helps companies to innovate, gain market- and business insights and to distinguish themselves in ways that cannot be done otherwise (LaValle, et al., 2011; McAfee & Brynjolfsson, 2012).

Data analysis is not new to the business environment. Still, Big Data analysis is considered to be a fundamental technological change. The difference between traditional business- and Big Data analysis is captured in the word 'big'. These days, datasets have become much larger due to ever-declining costs of data collection, storage and processing (Vahn, 2014). This makes that Big Data is distinguished from traditional data by three characteristics: volume, velocity and variety. The first two refer to the enormous amount of available data and its (almost) exponential speed of creation. Variety means that Big Data includes multiple data types (McAfee & Brynjolfsson, 2012; Lugmayr, et al., 2017).

Traditional computing environments and data analysis techniques cannot deal with these large datasets, and therefore new techniques to process Big Data have been developed (Costello & Prohaska, 2013; McAfee & Brynjolfsson, 2012). A challenge for many companies is to figure out how these new techniques can help them to utilise the value of Big Data (LaValle, et al., 2011). Following the information tech companies, less data intensive sectors are exploring new possible data sources and applications to profit from Big Data, likewise Damen Shipyards (Damen).

1.2 Automatic Identification System

A potential source of data that can be used for a wide range of applications in which Damen is interested, is derived from the Automatic Identification System (AIS). AIS data includes among others information about identification, location, speed, course, date and time of approximately 200.000 vessels worldwide, and has a velocity of more than 1 gigabyte per hour (Made Smart Group, 2017). The system automatically shares this information with other vessels and shore authorities. Since 2004, the International Maritime

Organization (IMO) obliges a wide range of vessels to be equipped with an AIS transponder as part of Regulation 19 of SOLAS Chapter V (IMO, 2017a), resulting in a comprehensive (historical) dataset.

Initially AIS was introduced for collision avoidance, but it was soon found out that AIS data can be used for many more applications such as analysing ship movements, shipping patterns, etc. (Harati-Mokhtari, et al., 2007; Aarseather & Moan, 2009; Wu, et al., 2017). These type of applications may have a great potential for market- and business intelligence solutions.

1.3 Damen Shipyards

Damen is a global shipyard group with a unique business concept for the shipbuilding industry. They keep standardised vessels in stock in order to significantly reduce delivery times. This concept gives Damen a great competitive advantage, but is not without risk since Damen must speculatively build vessels beforehand. This makes it extremely important for Damen to forecast the market and future vessel demand.

Therefore, Damen wants to investigate if it is possible to use AIS data, in combination with wind and sea state data, to measure, forecast and optimise vessel demand for a wide range of operations. This may help Damen to gain new market- and product insights. For this purpose, Damen wants to develop a case for the offshore wind market for which they supply Crew Transfer Vessels (CTVs). These vessels are needed for Crew Transfer Operations (CTOs) – transferring technicians, tools and small spare parts to and from wind turbines – throughout the whole lifecycle of offshore wind farms. The case should model CTV demand for CTOs in the offshore wind industry.

1.4 Made Smart Group

Made Smart Group (MSG) is an information service provider specialised in nautical information for the global maritime industry. MSG's customers use their information products on a day-to-day basis in Operational Control Centres, strategically for market- and business intelligence, and incident- and performance analysis. One of the many data sources used by MSG is derived from the ship born AIS systems, and MSG maintains the world's largest (historical) AIS database. Other significant data sources used by MSG include the Hydrographic Office for official nautical chart data, global weather data (historical and forecast) and a diversity of global sea state data (historical and forecast). The expertise and data of MSG is complementary to Damen's market and product knowledge for the offshore wind case. Furthermore, both parties are interested in the commercial value of Big Data analysis for this and other cases. For these reasons, Damen and MSG joined forces for this research.

1.5 Offshore Wind

The offshore wind industry is chosen for the case for two reasons. First, as mentioned, Damen is a major supplier of CTVs that are required for CTOs in the offshore wind industry. Therefore, Damen wants to use this case to learn more about the operational profile of CTVs. This may help Damen to improve the functional specifications of their vessels, gain market insights, better serve clients, create competitive advantage and develop new business models.

Secondly, the offshore wind industry is growing rapidly. This growth is triggered by one of the major challenges of our time: the human impact on climate change. A key element of constraining climate change is the energy transition towards renewables. This results in a growing market for renewables, which is reflected in Figure 1.

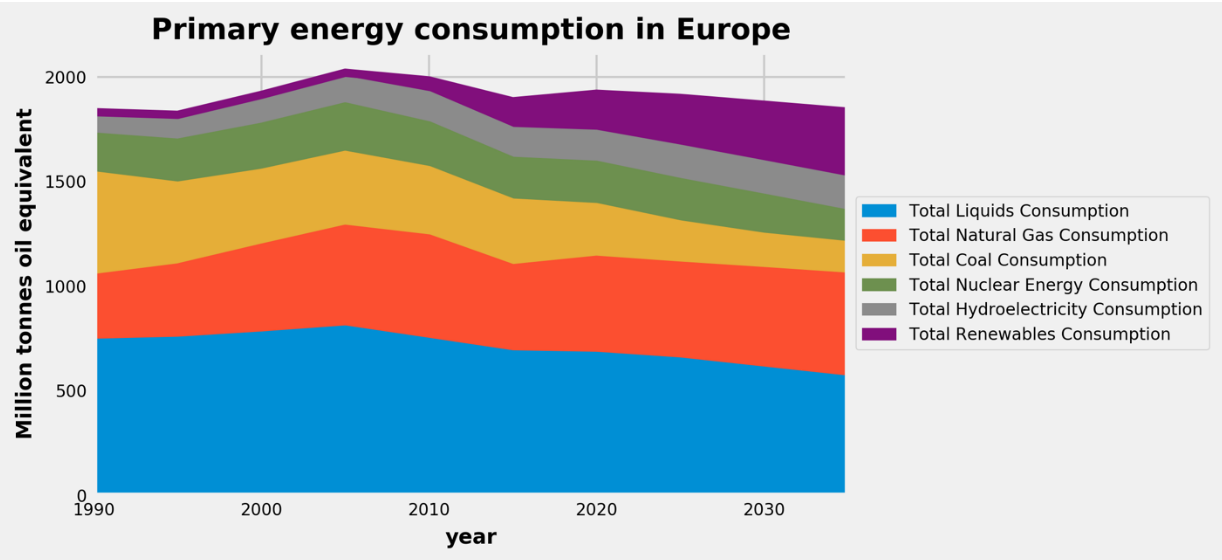

Figure 1: Forward and backward projection of the primary energy consumption in Europe. Data adopted from British Petroleum (2017), figure is own composition.

In Europe, offshore wind energy is a paramount contributor to the energy transition as it has the highest annual growing rate of all renewables (EY, 2015; WindEurope, 2017a). According to EY (2015), offshore wind has a great outlook for the future because it has an enormous energy potential and sites for onshore wind farms – currently the largest and cheapest renewable in Europe (WindEurope, 2017a) – are becoming scarcer, making offshore extensions necessary.

At the end of 2016, the European offshore wind capacity was 12.6 GW spread over 81 wind farms in 10 countries. This is just a humble beginning, as WindEurope (2017b) reports that this capacity will be extended to a total of 24.6 GW by 2020. Moreover, they state that a total of 65.5 GW of projects are currently in the pipeline. This is a significant market when realizing that a total investment of €18.2 billion was required to install 4.9 GW in 2016 (WindEurope, 2017b). Apart from Europe, other (upcoming) markets such as Asian countries and the US are investing in the offshore wind industry. According to EY (2015), the cumulated worldwide investment in offshore wind will be approximately €690 billion by 2040.

The market outlook is positive, which means that the market has potential for Damen to sell CTVs. 4C Offshore (2016) – a consultancy and market research firm – roughly estimates that the demand for CTVs for Operation and Maintenance (O&M) is approximately 1 vessel per year per 15 turbines. Although this number might be inaccurate (for future offshore wind farms), it indicates the significance of the CTV market. This number of 4C Offshore can be verified based on AIS data, which is part of this research. This, together with other and more precise market insights may help Damen to better serve the offshore wind market.

1.6 Objective

The objective of this project is to determine if and how Big Data analysis can be used to model (future) demand for Crew Transfer Vessels being used for Crew Transfer Operations in the offshore wind industry. The model should translate AIS, wind and sea state data, offshore wind farm specifications and Crew Transfer Vessel specifications into a Crew Transfer Vessel demand for servicing specific offshore wind farms. This model should provide insights into the Crew Transfer Vessel market for the offshore wind industry in terms of volume and timing. Furthermore, the project should provide insights into the operational profile of Crew Transfer Vessels.

1.7 Research Questions

Several research questions should be answered to meet the objective. The primary question to answer is how the CTV demand for CTOs in the offshore wind industry can be modelled primarily based on AIS, wind and sea state data. To answer this question, the following sub-questions should be answered first. From the offshore wind turbine-/ farm-side it should be known what the crew transfer demand is, and which parameters influence this. From the CTV-side it is needed to research the parameters limiting CTOs, such as the weather window. Furthermore, the CTO should be outlined in detail. It is necessary to know the logistic steps/ process of a CTO and be aware of the different strategies and their influence on the logistics. This information is necessary to derive Key Parameters (KP) and Key Performance Indicators (KPI) of the operation that are required to model the number of turbines that can be serviced by one CTV. Follow-up questions are which insights in terms of CTV market size and timing, and CTV performance and its operational profile can be drawn from the model results; and if it is possible to model vessel demand for other operations/ applications based on AIS data, similar to the CTV case.

1.8 Scope & Methodology

This project focuses on CTOs conducted with CTVs during the operation and maintenance phase of offshore wind farms. The number of included wind farms in the project will depend on the required time to add a wind farm to the analysis. At first, only 1 vessel servicing 1 wind farm is analysed to derive KPs and KPIs of the CTO process. Thereafter all CTVs servicing the initial wind farm are added to the analysis, then a second (third, fourth, etc.) wind farm will be added to increase the number of analysed CTOs and to show the possible influence of wind farm location on the KPs and KPIs. The final number of included wind farms and the timespan of AIS, wind and sea state data will be set in consultation with MSG and Damen, since the amount of available data is limited due to cost considerations.

All the relevant (background) information about the offshore wind turbines/ farms, CTOs and CTVs is collected via scientific literature, company and market reports, interviews with key-stakeholders including Damen, MSG, service operators and other relevant third parties. Furthermore, AIS data (of both Damen and non-Damen CTVs), wind and sea state data is used to derive the needed statistics for the analysis.

The used methodology of this project is based on the Cross-Industry Standard Process for Data Mining (CRISP-DM), which is a proven method to structure data mining projects (see Figure 2) (Shearer, 2000). The data preparation and modelling steps are reflected in Figure 3. AIS data, sea state data, offshore wind farm specifications and CTV specifications are used to derive the KPs and KPIs that are required to model CTV demand. These parameters are then used as input for the model. This, together with sea state statistics, offshore wind farms specifications and CTV specifications can be used to model CTV demand for specific wind farms. Furthermore, it provides insights into the operational profile of the used CTVs and the market size. The data is processed via scripts written in the open-source Python programming language. This language is widely used and among others excellent for data processing.

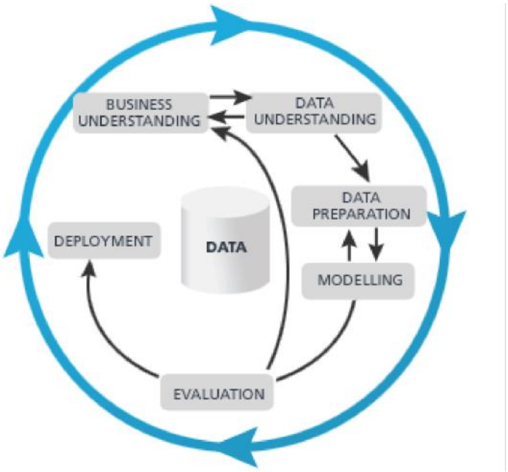

Figure 2: The Cross-Industry Standard Process for Data Mining model. Figure adopted from Shearer (2000, p. 14).

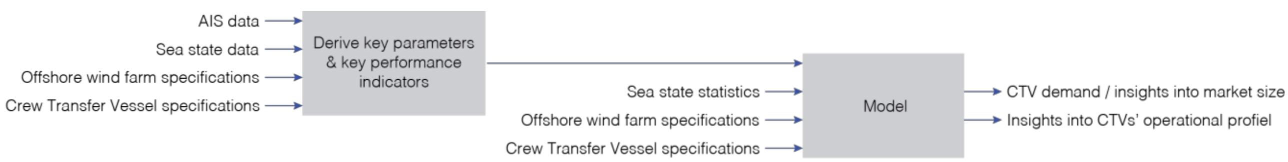

Figure 3: Data preparation & Modelling. Source: own composition.

It must be noticed that for this project a methodology is used, whereby the data is analysed before the model is composed. The data is analysed first to examine what kind of information can be obtained from the AIS data. Thereafter, the model is composed based on the available statistics derived from the AIS data. In more traditional projects is the model composed before the statistics are obtained, however, this project requires a different approach due to the novelty of AIS data analysis.

1.9 Thesis Outline

The outline of this thesis is as follows: the relevant information and specifications of offshore wind farms and the Crew Transfer Operation process are discussed in chapters 2 and 3. These two chapters form the business understanding of this project, and the presented information is among others required to understand which parameters influence the Crew Transfer Operation- demand of wind farms and supply of Crew Transfer Vessels. In chapter 4 three wind farms are selected that are used for the data analysis, and it is explained why these wind farms are suitable for the analysis. The required data for the analysis is collected and prepared in chapter 5, and mined with the algorithms presented in chapter 6. The statistical results of the datamining process are presented in chapter 7. These statistics are used as input for the Crew Transfer Vessel Demand Model, of which the logic is elaborated in chapter 8. Furthermore, the results of the model are presented in this chapter, including a validation and sensitivity analysis. In chapter 9 are two potential applications of the Crew Transfer Vessel Demand Model reviewed, and the final chapter 10 includes the conclusion and discussion of the research.

2 Offshore Wind Farms

Offshore wind farms need to be serviced, resulting in a crew transfer demand. Therefore, a profound understanding about offshore wind farms is relevant to understand the process of CTOs and is crucial to model CTV demand. This chapter focuses on the trends and crew transfer demand of offshore wind farms, with the objective to present the wind farm specifications and parameters influencing CTV demand. More background information about offshore wind (farms) is included in Appendix A.

2.1 Current & Future Wind Farms

Figure 4 shows an overview of the locations of current and future wind farms in the North Sea. The dark grey sites are fully commissioned wind farms and the white sites are in early development/ concept stage, and sites in between are under development/ construction. As can be seen only relatively few wind farms are fully commissioned, indicating future activity. Also, it can be noticed that the commissioned wind farms are located closer to the shore than other sites. The influence of latter is discussed in section 2.2.2.

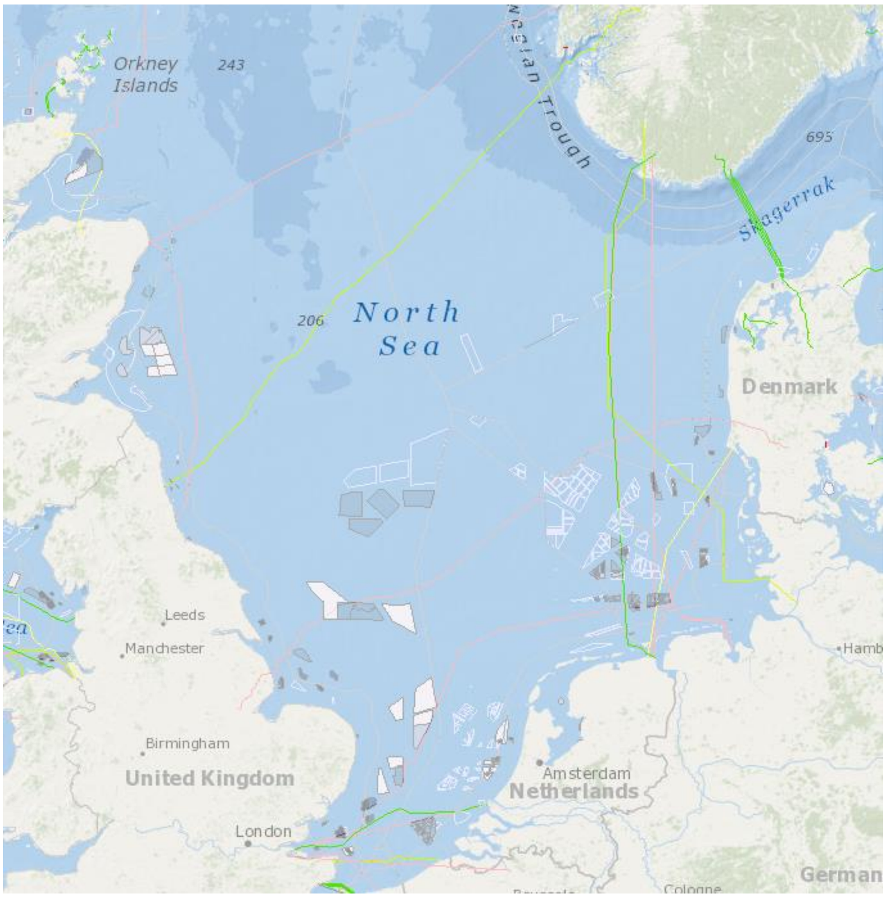

Figure 4: Offshore wind farm sites North Sea. Figure adopted from 4C Offshore (2017a).

2.2 Trends

The rapid (technological) development of the offshore wind industry results in some clear trends as regards offshore wind farm specifications on three subjects: capacity, location and turbine reliability. The latter is discussed in section 2.3.

2.2.1 Capacity

The capacity of offshore wind turbines has been growing significantly. In 1991, the first turbines had a capacity of less than 0.5 MW, whereas in 2016, the average installed turbine has a capacity of 4.8 MW. This upward trend is likely to continue, as the largest offshore turbines installed to date have a capacity of 8 MW (WindEurope, 2017b). This trend is of utmost importance for the offshore wind industry because it significantly helps to lower the Levelised Cost of Energy (LCOE) (see Appendix A.2) – and thus increases the competitiveness of offshore wind energy – by profiting from economies of scale (EY, 2015; Wiser, et al., 2016). The importance of this can already be noticed in the case of the first to be build subsidy-free DONG Energy wind farm, which is expected to have wind turbines with a capacity of 13-15 MW (Bloomberg, 2017). The downside of larger turbines is an increase of construction weight and size, which involves higher fabrication and installation costs. However, the benefits of large capacity turbines outweigh the extra costs (IRENA, 2012).

Another way to increase the capacity of an offshore wind farm is by increasing the number of turbines. Figure 5 is adopted from Shafiee et al. (2016) and shows the effect of the number of turbines on the LCOE of a virtual offshore wind farm with 5 MW turbines. As can be seen, the effect of economies of scale is particularly strong up to 100 turbines. Thereafter the effect is more modest, but still significant in absolute terms.

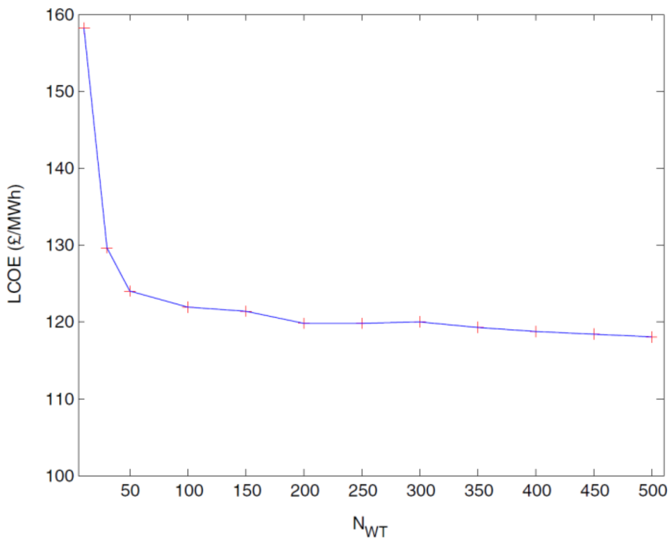

Figure 5: Effect of number of turbines (N_{WT}) on the LCOE.
Figure adopted from Shafiee et al. (2016, p. 974).

2.2.2 Location

The in 2016 grid-connected wind farms have an average water depth and distance to shore of respectively 29.2 m and 43.5 km. As can be seen in Figure 6, new wind farms tend to be located further from the shore and in deeper waters, which has a major influence on the Capital Expenditure (CAPEX) and Operational Expenditure (OPEX) (Breton & Moe, 2009; Carroll, et al., 2017; Dalgic, et al., 2015b). Shafiee et al. (2016) even sate that the LCOE increases around 11% when the distance between shore and wind farm is doubled.

Extra CAPEX of deep-sea wind farms is mainly caused by more complex turbine foundations and difficulty of installation. IRENA (2012) points out that the costs for fixed seabed foundations are becoming increasingly expensive for water depths above 20 m, and becomes uneconomical for water depths above 40 m. Although floating foundations are nowadays more expensive than fixed seabed foundations, IRENA (2012) believes that the potential for cost reductions of floating foundations is much greater than those for fixed seabed foundations, making floating foundations the economical solution for wind farms in deeper waters in the future.

Other extra OPEX and CAPEX are related to an increasing wind farm to shore distance. These costs are mainly caused by longer transit times (which results in longer durations of installation and maintenance tasks), harsher sea states (which is detrimental for the accessibility of wind farms and turbine uptime) and the necessity of longer power cables to connect the wind farm to the grid (Shafiee, et al., 2016; IRENA, 2012).

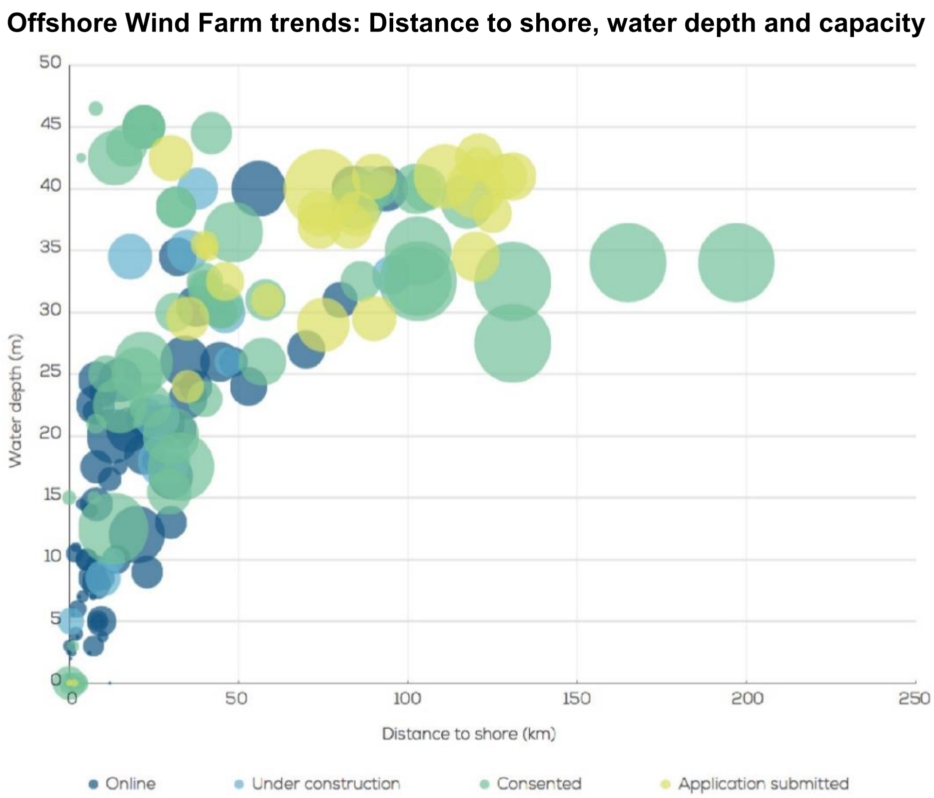

Figure 6: Average water depth and distance to shore of bottom-fixed wind farms sorted by development status. The size of the circle indicates the capacity. Figure adopted from WindEurope (2017b, p. 29).

2.2.3 The future of remote control & robotics

In the (near) future, a part of the maintenance operations may be executed by, or with the help of robots. Turbines can now be monitored and reset remotely resulting is less CTOs required. This is a quite simple solution, but other more challenging projects are under development. The turbine blades for example, can be inspected by making use of automated drone technology, instead of hoisting technicians with large cranes along the turbine blades (Offshore Wind Industry, 2017). At the end of 2017, a consortium of five top universities from the UK was founded with the aim to develop robotics and artificial intelligence technologies for the O&M of offshore wind assets (OffshoreWind.biz, 2017a). This may help to further decrease the necessity of human access in the further, and thereby the number of required CTVs.

2.3 Crew Transfer Demand

Crew transfer demand is a crucially important input variable when modelling CTV demand. However, it is not possible to give an unambiguous number of required crew transfers per turbine per year, since the demand is primarily correlated with annual service activities and turbine failure rates (Crabtree, et al., 2015; Carroll, et al., 2016; Dinwoodie, et al., 2015). This section presents a carefully considered number based on a literature review. Moreover, in a later section of this thesis, the AIS data is used to count the number of visits at each turbine. The latter is used as input for the crew transfer demand model.

2.3.1 Difficulties of providing turbine failure rates

Turbine failure rates are dynamic and influenced by several factors. First of all, turbines change over time due to technological development (Carroll, et al., 2015; Carroll, et al., 2017). This evidently results in different failure rates between turbines generations. Mostly in the positive sense, however, not always as increasing capacities and new complex systems may involve new challenges (Faulstich, et al., 2011; Yang, et al., 2015). Furthermore, Carroll et al. (2017) demonstrate that failure rates can differ per drivetrain configuration. They found that turbines with permanent magnet generators and fully rated power converters have the lowest failure rates. It is probably for this reason that most (but not all) offshore turbines have this drivetrain configuration.

Secondly, failure rates are dynamic over the lifetime of turbines due to wear and tear of components. This normal failure distribution is often described by the bathtub curve, which describes high failure rates in the early lifetime due to teething problems, constant relatively low failure rates during the long useful life and again high failure rates during the wear out period of a turbine (Faulstich, et al., 2011). This bathtub curve is not reflected in Figure 7 from 4C Offshore (2016). This figure illustrates a nearly opposite effect of the wind farm age on the CTV demand based on data from O&M activities carried out in 2015. Of course, the presented relation is for this particular point in time and may change when the wind farm population changes. The contradiction between the bathtub curve and the relation found by 4C Offshore illustrates the lack of knowledge about the relation between turbine age and maintenance requirements.

Third, failure rates are significantly influenced by weather conditions, as there is a strong correlation between average failure rate and average wind speed (Carroll, et al., 2016). Since wind speed distributions vary between wind farm sites and years, the average failure rate also varies. Climate change may have an effect on turbine failure as well. The hurricane that hit Ireland in fall 2017 is an example of this. Ireland is normally not hit by hurricanes. Evident, a hurricane could destroy complete offshore wind farms.

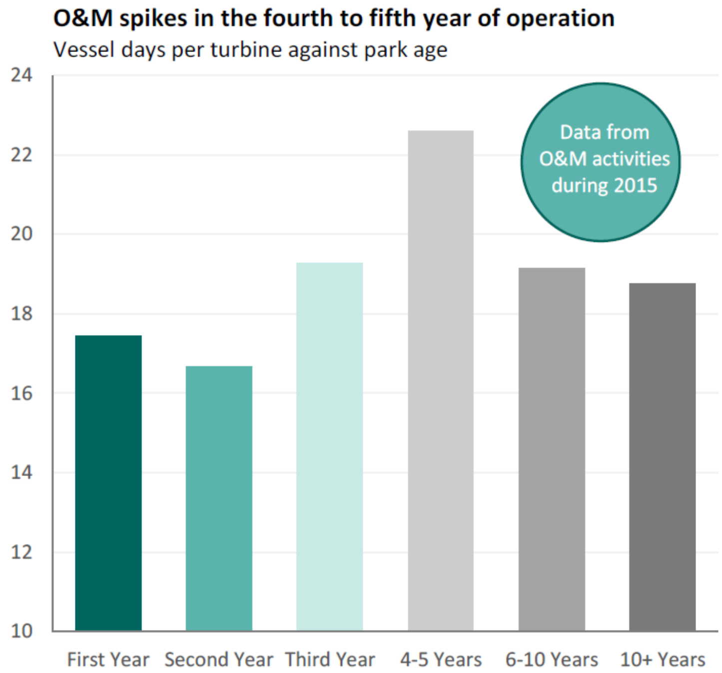

Figure 7: Influence of wind farm age on CTV Demand. Figure adopted from 4C Offshore (2016, p. 50)

Another difficulty is a lack of publicly available statistical data on offshore turbine failure rates. Crabtree et al. (2015) point out that for commercial reasons, manufacturers and operators are very reserved when it comes to disclosing data on this domain. Consequently, scientific literature on offshore turbine reliability is limited and older articles are frequently based on data from onshore turbines. As offshore turbines are often equipped with different drivetrain configurations than onshore turbines (Carroll, et al., 2017) and are exposed to harsher weather conditions, the usability of onshore data should be questioned.

2.3.2 Transfers per turbine: literature

Figure 8 shows three different demands for CTV visits per turbine per year, which are calculated based on Dinwoodie et al. (2015), Sperstad et al. (2016) and Carroll et al. (2016). All three papers present numbers about the occurrence of O&M events and the required technician time per event (see Table 1). In Figure 8, one CTV visit represents one drop-off and one pick-up of technicians. So, the number of transfers (drop-off or pick-up) is twice as much. Although the range in Figure 8 seems narrow, the difference is significant. For a 100-turbine wind farm the number of required CTV visits per year is according to Sperstad et al. (2016) and Carroll et al. (2016) respectively 2220 and 2607. The difference is around 387 CTV visits per year. The following part discusses the figures used for the calculations to get a better understanding of what caused these differences.

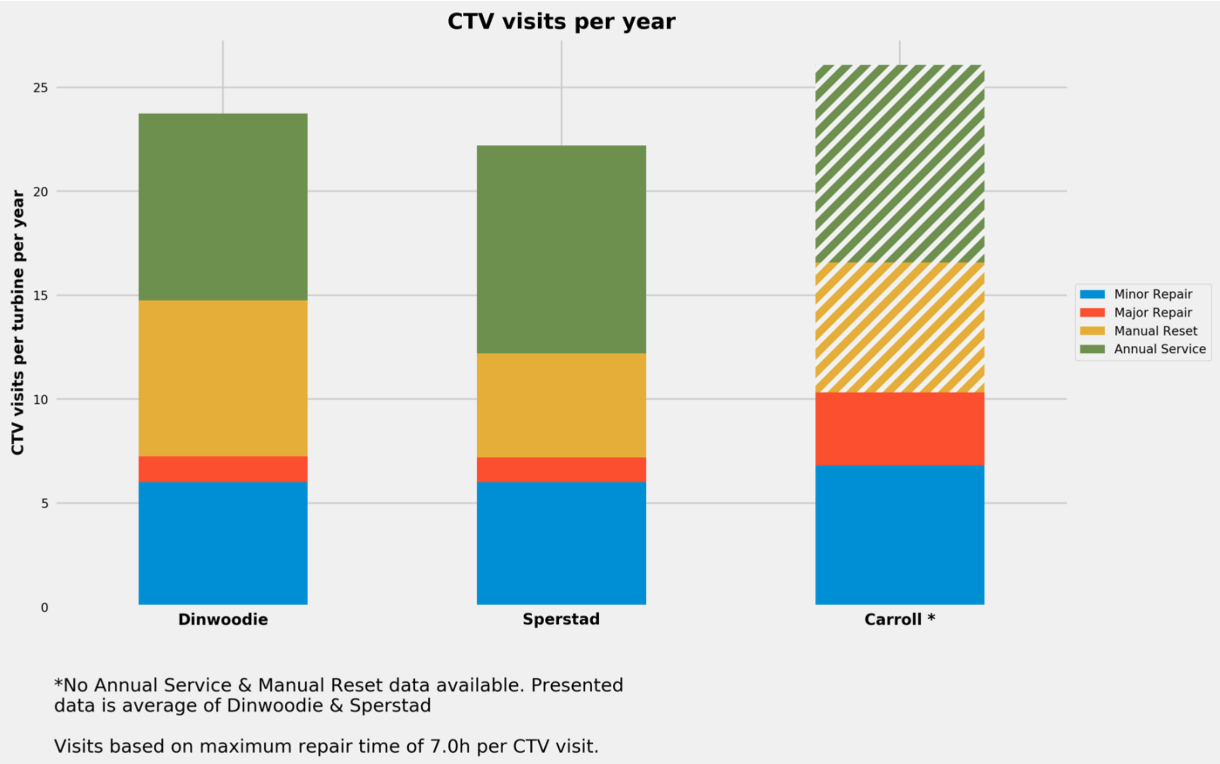

Figure 8: Required CTV visits per turbine per year. Source: own composition.

Table 1: Events per turbine per year. Data adopted from Dinwoodie et al. (2015, p. 12), Sperstad et al. (2016, p. 263), and Carroll et al. (2016, p. 1117), table is own composition.

	Manual Reset			Minor Repair			Major repair			Major Replacement			Annual Service		
	Dinwoodie	Sperstad	Carroll	Dinwoodie	Sperstad	Carroll	Dinwoodie	Sperstad	Carroll	Dinwoodie	Sperstad	Carroll	Dinwoodie	Sperstad	Carroll
Events / turbine / year	7.5	5	-	3	3	6.81	0.31	0.3	1.17	0.08	0.11	0.29	1	n/a	-
Active maintenance time [h]	3	3	-	7.5	7.5	6.67	24	22	17.64	52	34	116.19	60	70	-
Technicians required	2	1	-	2	3	2.61	3.5	5	3.44	5	n/a	9.14	3	3	-
Vessel Required	CTV	CTV	-	CTV	CTV	-	CTV / SOV	CTV	-	Heavy-Lift Vessel	Jack-Up Vessel	-	CTV	CTV	-

Dinwoodie et al. (2015) present figures that are *"… provided by a developer based on their expert knowledge and are representative expectations for the current generation of offshore turbines"* (p. 4). The paper does not provide any further information about the developer, the wind farm population to which these figures apply, and the underlying methodology about how the developer collected these figures. The lack of information makes it hard to judge the correctness of these figures. The figures of Dinwoodie et al. form the basis of the figures presented by Sperstad et al. (2016) – hence the similarities – which indicates some level of correctness as is explained in the next paragraph.

Sperstad et al. (2016) adopted their figures from a report of the International Energy Agency, of which Sperstad is a co-author (Smart, et al., 2016). As mentioned, the figures are based on those of Dinwoodie et al. (2015), however, small adjustments are made based on input from industry players and consultancy. The following is based on the report of Smart et al. (2016), because they elaborate more than the paper on the reasoning behind the adjustments. As can be seen in Table 1, the first relevant difference for CTV demand is the number of required manual resets, i.e. brief visits to inspect/ reset the turbine systems. Fraunhofer IWES advised Smart et al. (2016) to lower the occurrence, since turbine resets has been shifting from manual to remote resets. Another significant difference is annual service duration, which is slightly higher according to Smart el al. (2016). Based on input from SINTEF, Smart el al. (2016) state that 4-5 MW turbines and 5-6 MW turbines require respectively 50 and 60 annual service hours. On top of that, they account some hours for structure inspections, in which time related maintenance is averaged. The 70 hours presented by Sperstad et al. (2016) is therefore most likely representative for modern 5-6 MW turbines. Other differences do not significantly influence CTV demand.

The paper of Carroll et al. (2016) is the only one of these three that is directly based on operational data, as the figures are statistics from approximately 350 offshore turbines from a leading manufacturer. In total, the dataset consists of over 1768 operational turbine years. The turbines are installed in Europe and have a capacity between 2 and 4 MW. Exact specifications are not given in the paper for confidentiality reasons. According to Carroll et al. (2016), their research is unique because they were able to analyse data from a large modern turbine population, however, the novelty of the turbines can be questioned as current turbine capacities are much higher as mentioned in section 2.2.1. In theory, the turbine reliability is uncorrelated to turbine capacity. However, based on a study of 6,000 0.3 MW to 1.8 MW onshore turbines it turned out that the high capacity turbines failed more often. It is assumed that this effect is cause by the novelty of high capacity turbine designs (Yang, et al., 2015). This may mean that Carroll et al. (2016) figures should be scaled/ adapted to represent larger modern turbines.

There are several aspects that may cause the differences between the three papers. First of all, input data differs between the papers. Second, each author may have defined the events slightly different, which could result in different numbers. Dinwoodie et al. (2015) for example, present in their paper an extra event type: medium repair. This category is added to major repairs in the other papers, as well as in Table 1. Third, the turbine population, time interval and weather conditions to which the turbines are exposed are probably different between the papers, which has a major influence on turbine failure rates for aforementioned reasons. Fourth, there are different O&M strategies – e.g. preventive vs responsive – that may influence the number of required annual service visits and failure rates.

Based on the literature, it can be concluded that each turbine requires between 24 to 26 CTV visits per turbine per year (this is 48-52 crew transfers, when assuming that each visit consists out of 1 drop-off and 1 pick-up of technicians). Manual resets and annual service are only reviewed by Dinwoodie et al. (2015) and Sperstad et al. (2016), of which the latter made adjustments for modern turbines (less manual resets and more annual service hours for large 5-6 MW turbines). Therefore, the figures for manual resets and annual service are adopted from Sperstad et al. (2016). Carroll et al. (2016) estimate the number of minor and major repairs significantly higher than Dinwoodie et al. (2015) and Sperstad et al. (2016). For these events, the figures from Carroll et al. (2016) are adopted, since they are based on statistics rather than expert knowledge. However, they may have to be increased slightly for modern 5-6 MW turbines. This results in 24-26 required CTV visits per turbine per year.

Aforementioned, 4C Offshore states that 1 CTV is needed per 15 turbines. 15 turbines multiplied by 25 visits equals 375 CTOs per vessel per year. This is only around 1.05 transfers per day (assuming that a CTV is 80% of the days operational). This number seems quite low, even if the number of operational days would be halved due to accessibility of the wind farm. The AIS data is used to verify these numbers in a latter section of this thesis.

2.3.3 Transfers per turbine: operators

SeaZip is an offshore service company that owns and operates six Damen FCS 2610 vessels. An interview with Mr. Arends and Mr. Van Der Star – SeaZip's managing owner and managing partner – confirms that there is no unambiguous number of required crew transfers per turbine per year. According to them, the number of crew transfers has an enormous variance caused by different activities, turbines, wind farms, etc. Sometimes SeaZip's vessels sail to a wind farm to visit one turbine while it also occurs that they execute around 1000 transfers per month. For this reason, SeaZip does not know how many transfers a turbine demands per year.

SPARTA (2017) is a joint industry project of leading offshore wind operators in the UK. In this project, they have monitored 1,378 offshore wind turbines, which is 93.7% of the installed capacity in the UK in 2016. Figure 9 shows the average monthly repair rate of this turbine population. On average, this is 15.84 repairs per turbine per year. The project does not tell how many transfers are needed to carry out these repairs. When roughly assuming that a repair requires 1.5 - 2.0 visits on average, the number of transfers per turbine per year for repairs is 48 - 64. This rough estimation is based on the required repair times presented in Table 1. It is not clear from the paper if the planned maintenance is included in the repair rates presented in the figure.

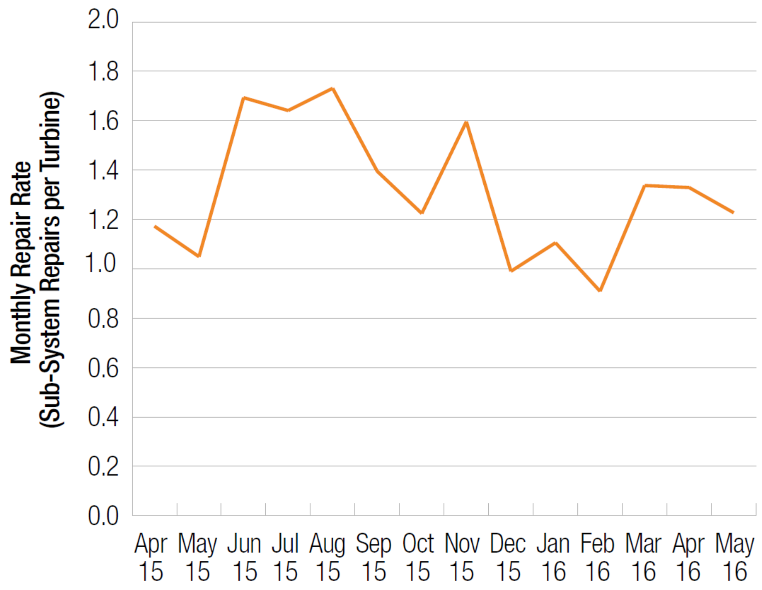

Figure 9: Average monthly repair rate of 1,378 offshore turbines in the UK. Figure adopted from SPARTA (2017, p. 8)

2.4 Relevant Wind Farm Specifications

As discussed in this chapter, the serviced wind farms significantly influence CTOs. The wind farm specifications in Table 2 are considered to be relevant for the CTV demand, and therefore used for the model. Of these specifications, the wind farm age is a special case. The primary influence of wind turbine age on CTV demand is turbine reliability and varying maintenance requirements. However, as is explained in section 2.3.1, there is a lack of publicly available data and knowledge about this. Therefore, it is unfortunately not possible to model CTV demand whereby age-related effects are taken into account. The effect of this is that the model will provide an average number of CTVs required to perform the maintenance tasks, instead of a specific demand per year.

Table 2: Relevance wind farm specifications for analysing CTV demand. Source: own composition.

Specification	Relevance for CTV demand
Location // Distance to port	The transit time between shore and wind farm has a major influence on the operational hours within the wind farm (Shafiee, et al., 2016; 4C Offshore, 2016; Carroll, et al., 2017).
Location // GPS coordinates	GPS coordinates are important for the AIS analysis, since this can be used to indicate whether a CTV is in a wind farm, near a turbine or somewhere else.
Location // Sea state	Wind farms accessibility is to the utmost extend influenced by sea state conditions (Shafiee, et al., 2016; 4C Offshore, 2016; Dalgic, et al., 2015b).
Number of turbines	It is expected that each turbine requires an average number of visits per year. Therefore, the number of turbines is relevant to calculate the CTO demand (Dalgic, et al., 2015a; Carroll, et al., 2016; Dinwoodie, et al., 2015).
Wind farm age	The age of a wind farm will affect the number of required visits during the operational phase due to different turbine design and the dynamic lifetime failure distribution (Carroll, et al., 2015; Carroll, et al., 2017; Faulstich, et al., 2011).

This chapter focused on crew transfer demand, which is correlated to the to be serviced wind farm. The following chapter discusses the supply side of this demand, namely how CTVs are deployed to execute crew transfers.

3 Key Parameters & Key Performance Indicators of Crew Transfer Operations

A Crew Transfer Operation (CTO) is an operation whereby people are transferred between offshore structures and the shore. These operations are frequent in the offshore wind industry, as turbines need to be accessed for a wide range of activities during their whole lifecycle (Dalgic, et al., 2015a; Shafiee, 2015a). This chapter outlines CTOs in the offshore wind industry in-depth, with the aim to identify the required Key Parameters (KPs) and Key Performance Indicators (KPIs) of CTOs needed to model CTV demand.

3.1 Modes of Transport

Currently, CTVs are the most common used mode of transport for accessing offshore wind turbines. These vessels provide an economical solution for transferring technicians, tools and small spare parts during the construction and operational phase of offshore wind farms (4C Offshore, 2016; ECN, 2016; Dalgic, et al., 2015b). However, the operational profile of CTVs is limited, hence the necessity of complementary material.

Other used modes of transport are Service Operations Vessels (SOVs) and helicopters (Dalgic, et al., 2015b; 4C Offshore, 2016; ECN, 2016). Although this project solely focuses on CTVs, it is relevant to compare the different modes of transport to get a comprehensive understanding of CTOs. An overview of the most relevant typical operational characteristics of all three modes of transport is presented in Table 3.

Table 3: Operational profile of modes of transport. Data from 4C Offshore (2016), ECN (2016) and Smart et al. (2016), table is own composition.

	CTV	SOV	Helicopter
Max. Hs during transfers	1.5 m – 1.8 m	2.5 m - 3.0 m	n.a.
Operational hours	Daylight preferred	24 hours	Daylight restricted
Ability to remain at sea for multiple days	No	Yes	No
Components/ spare part transfer	0.4t, 15 m crane	3t, 20 m crane	n.a.
Number of technicians	12	45 - 60	6
Maximum speed	25 kts	10 kts	65 kts

3.1.1 Crew Transfer Vessels

For this project, CTVs are defined as specialised vessels for transporting industrial personnel to and from offshore structures. CTVs used in the offshore wind industry are typically small (up to 30 m) double hull vessels; have a maximum speed around 25 knots (kts); and can execute CTOs in mean significant wave heights (Hs) up to 1.5 - 1.8 m. The maximum Hs together with long transit times between the shore and remote wind farms are the main limiting factors of CTVs' employability (Dalgic, et al., 2015a; Dalgic, et al., 2015b). More information about CTVs is included in section 3.2.

3.1.2 Service Operations Vessels

SOVs are typically vessels under 85 m; can accommodate up to 60 technicians; and are equipped with heave compensated gangways. The latter allows safe access to turbines in significant wave heights up to 3.0 m, which is important since limited turbine accessibility due to severe weather conditions is a major contributor to the downtime of wind farms (ECN, 2016; Dalgic, et al., 2015b). Another advantage of SOVs is the ability to remain at sea for multiple weeks in a row whereas CTVs should go back to the port/ maintenance hub on a regular basis (4C Offshore, 2016). The gained time savings are significant, especially for newer wind farms that tend to move away further from the shore (WindEurope, 2017b). Finally, SOVs can carry more equipment and have larger crane capacities than CTVs, which increases their scope of activities. For some projects SOVs are more economical and/ or the advantages of SOVs outweigh their relatively high costs (4C Offshore, 2016; ECN, 2016).

3.1.3 Helicopters

Helicopters are extremely expensive per operational hour (€2,500 versus €500 for a CTV (4C Offshore, 2016)), hence they are normally only used when response time is critical and/ or weather conditions make CTV and SOV access impossible (4C Offshore, 2016; Dalgic, et al., 2015b). It is known from statistics in the oil and gas industry that helicopter transfers are the riskiest activity for offshore workers (Tavner, 2012), which encourages minimising helicopter usage.

As aforementioned suggests, the choice which mode of transport to use is strongly dependent on parameters such as distance between port and wind farm, sea state and type/ criticality of maintenance activities. It is not unusual for wind farm operators to deploy a strategy in which multiple modes of transport are used, since the operational profiles of the material is complementary (4C Offshore, 2016; Dalgic, et al., 2015b). More information about O&M strategies is included in section 3.3.

3.2 Crew Transfer Vessels

'Crew Transfer Vessel' is a collective name rather than one specific vessel type. This section describes the different configurations, most important specifications and regulations that apply to CTVs.

3.2.1 Crew Transfer Vessel designs

There is a wide range of CTV designs on the market, with all different specifications, advantages and disadvantages. According to 4C Offshore (2016) there are three primary CTV design features. First, the safety and comfort of turbine technicians should be guaranteed. Safety is an evident requirement and comfort refers here to seasickness precaution, which is important because seasickness has a not to be underestimated effect on technicians' performance (ECN, 2016). The second feature is turbine accessibility. Aforementioned, wind farms tend to move away further from the shore, resulting in increasing transit distances and severer sea state conditions. This could be detrimental to the operational window of CTVs, and should therefore be addressed. The last feature is operational capability/ efficiency. Naturally, wind farm operators prefer lower CTV costs without compromising on operational output.

The clearest difference between CTV designs is the hull shape. In general, there are four different hull configurations used for CTOs in the offshore wind industry: RIB, monohull, catamaran and Small Waterplane Area Twin Hull (SWATH) (see Figure 10). The RIB is barely used, while the catamaran configuration is the most common and preferred by the majority of operators (Dalgic, et al., 2015a; Tavner, 2012). This preference is reflected in Figure 11, which clearly shows that the largest share of added CTVs are aluminium catamarans.

Catamarans are characterised by high speed, low fuel consumption, low running costs and good seakeeping performance. Downside of catamarans is the limited cargo capacity and that waves higher than a certain level could be detrimental to the seakeeping performance due to slamming (Dalgic, et al., 2015a; 4C Offshore, 2016; ECN, 2016). Most of these characteristics apply to SWATHs as well, however, they require more power which is detrimental to fuel and running costs and their manoeuvrability is less good (4C Offshore, 2016). An overview of the characteristics of the different configurations (RIB not included) is depicted in Table 4.

(a)

(b)

(c)

(d)

Figure 10: CTV configurations used on the offshore wind industry. (a) RIB, (b) monohull, (c) catamaran and (d) SWATH. Images adopted from ESVAGT (2017), Damen (2017) and CWind (2017).

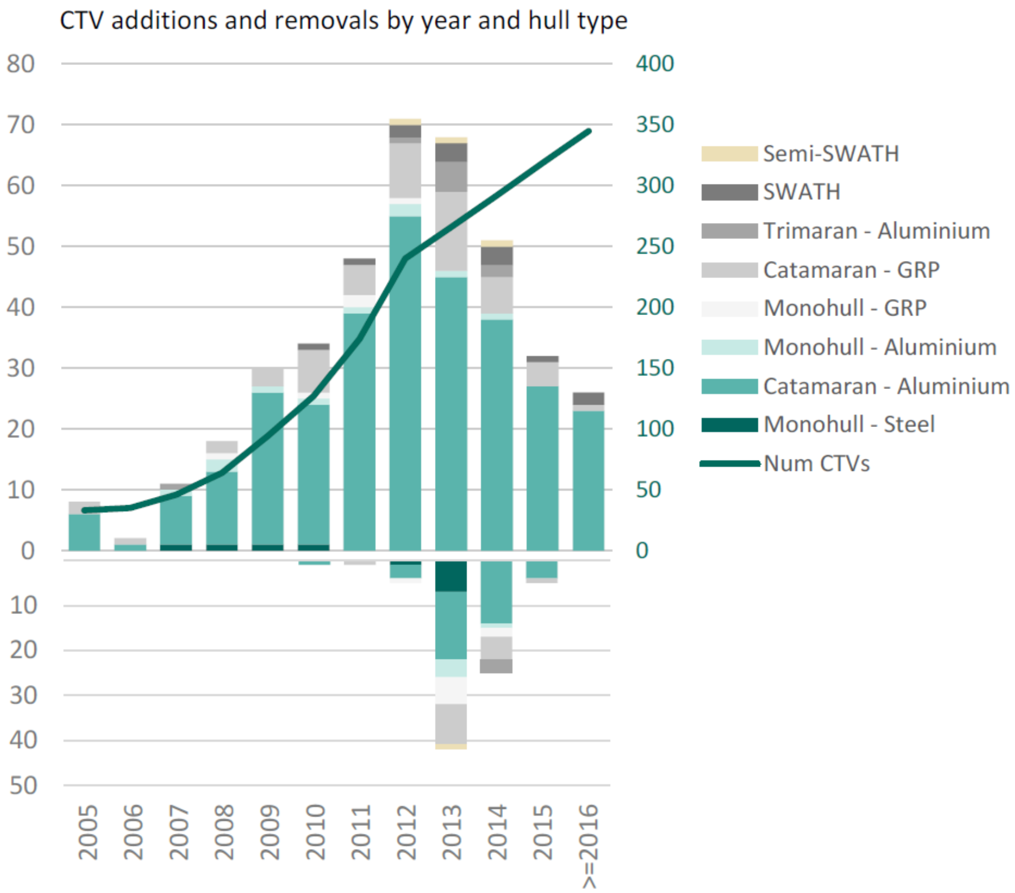

Figure 11: CTV additions and removals. Figure adopted from 4C Offshore (2016, p. 24)

Table 4: Advantages and disadvantages of hull configurations. Information adopted from Dalgic et al. (2015a, p. 33), table is own composition.

	Advantages	Disadvantages
Monohull	+ Relatively low charter costs + Low fuel consumption + High market availability	- Limited technician capacity (6-8) - Low comfortability for technicians - Crew transfers up to 1 m Hs
Catamaran	+ Crew transfers up to 1.5 m Hs	- Limited technician capacity (±12) - High charter rates
SWATH	+ High technician capacity (12-60) + Crew transfers up to 1.5 m Hs + High comfortability for technicians	- Limited market availability - High charter rates

* The majority of CTVs (all configurations) have a length of 14 to 28 m (4C Offshore, 2017b).

3.2.2 Crew Transfer Vessel specifications

According to Damen (2014) important specification categories of CTVs are dimensions, capacities, performance and machinery. For this project, the most important two specifications are the number of technicians and the vessels speed. Other specifications such as cargo deck and crane capacity, seakeeping performance, and the ability to remain at sea for longer times are important specifications for the CTV usages as well, but not needed for this project. Technical specifications such as the engine types are of course interesting for offshore service operators, but not required for this project. Appendix D includes an overview of the main CTV specifications that are available of the vessels that were under contract in the selected wind farms in 2016.

3.2.3 Design & Automatic Identification Systems regulations

Current regulations from the IMO prescribe that CTVs may not carry more than 12 persons (excl. vessels' crew) and cannot exceed a Load Line Length of 24 m. Otherwise they are classified as passenger ships, which entails more comprehensive regulations (IMO, 2017b). These regulations are not adopted for this project since the IMO announced that they will make an exemption of these regulations for transporting industrial personnel in the course of 2017 (however, this is still not done at the end of 2017), and some flag states already imposed new regulations allowing CTVs to transport more than 12 persons when sailing in national waters (4C Offshore, 2016). As a result, Damen notices that nowadays the requested number of passengers and vessel length is demand driven rather than regulations driven. Hence, they are currently developing a new fast crew supplier for the offshore wind industry.

Since 31 December 2004, the IMO prescribe *"… AIS to be fitted aboard all ships of 300 gross tonnage and upwards engaged on international voyages, cargo ships of 500 gross tonnage and upwards not engaged on international voyages and all passenger ships irrespective of size"* (IMO, 2017a). A Damen

FCS 2610 is neither above 300 gross tonnage nor a passenger ship under the aforementioned regulations. This means that a Damen FCS 2610 – and most other CTVs – are not obliged to fit an AIS transponder. However, SeaZip states that in practice almost all CTVs are equipped with AIS transponders. They state that it is nowadays the industry standard, and that wind farm owners often require CTVs working in their wind farm to be equipped with AIS transponders. This does not alter that not all CTVs are necessarily equipped with AIS/ turned on their AIS. CTVs that do not transmit an AIS signal cannot be included in the analysis of this research.

3.3 Operations & Maintenance Strategies

O&M strategies are strongly dependent on wind farm location, as transit time and turbine accessibility are determining factors for the used material. Wind farms close to the shore can be serviced with CTVs operating from onshore maintenance hubs, whereas for wind farms located further from the shore strategies with SOVs and/ or offshore maintenance hubs from where CTVs operate are more suitable (4C Offshore, 2016; Tavner, 2012; Shafiee, 2015a). For remote sites, an offshore maintenance hub strategy could minimise reaction time to turbine failures and thereby downtime, fuel costs and transit times (Dalgic, et al., 2015c).

4C Offshore (2016) conducted a research into all significant European projects, and found that: CTV-based strategies dominate for wind farms up to 30 km from port; wind farms located between 30 and 65 km from port are primarily serviced with a combination of CTVs and helicopters; and sites located 65 km and over from port are typically serviced with SOVs and CTVs. These findings are partly in line with Tavner (2012), who states that the transit time for offshore wind farms located further than 74 km from the port becomes too long to service them with CTVs from an onshore maintenance hub. SeaZip states that the maximum preferred transit time is about 1.5 hours (±55 km when sailing with an average speed of 20 kts). When exceeding this time, an offshore maintenance hub becomes a more attractive solution according to SeaZip.

Apart from the used material, also the choice/ balance between preventive and corrective maintenance is an important strategical O&M decision. This mainly influences the timing of material, and not particularly the type of material (Irawan, et al., 2017). During summer campaigns for example, the demand for CTVs is relatively high in order to conduct the planned preventive maintenance of the turbines.

3.4 Logistics

This section outlines the logistics of CTOs. A profound understanding of this is required to effectively develop algorithms for translating AIS data into relevant information about CTOs. First, the process is discussed followed by the weather window of the operations.

3.4.1 Process steps

SeaZip states that a CTV is basically a taxi for technicians. In the morning, it sails from the port/ offshore maintenance hub to the wind farm to drop-off technicians at several turbines. When the technicians finished their tasks on the turbine, the CTV picks them up and brings them to the next turbine. This continues till the end of the day/ shift, thereafter the CTV sails back to the port/ offshore maintenance hub. This process, including the speed profile of a CTV and its location is visualised in Figure 12 on page 24.

After picking up/ dropping of technicians at a turbine two events could occur. First, the CTV sails to another turbine to pick-up/ drop-off technicians. Second, the CTV must wait until the technicians finished their tasks on the turbines. In this case, the CTV is idle and generally drifts until the technicians are done. In many wind farms CTVs are obliged to leave the wind farm area when idle and a few wind farms have special mooring buoys for idle CTVs. It may also occur that CTVs moor to a turbine when idle.

A transfer itself could go very fast (30 to 60 seconds) according to SeaZip, however, this is among others dependent on the weather conditions and if spare parts need to be transferred. During this time, a 'normal' maintenance team consisting of 3 to 4 technicians could step over from the CTV to the turbine. Approaching, docking and leaving the turbine is not included in this time.

Smart et al. (2016) state the following about the required time for crew transfers based on industry experience of the SINTEF Energy Research: *"The transfer time is the average time needed for transfer of technicians from a vessel to a wind turbine or vice versa. This includes travel within the wind farm (on average 5 rotor diameters of travel from one random position in the farm to another for 100 turbines, given 7 minutes of travel for each transfer), approaching and docking to the turbine (5 minutes), transferring the technicians (5 minutes for transferring two or three technicians), and lifting/ hoisting of small parts or consumables (5 minutes)"* (p. 19). Although the time for transferring the technicians significantly differs between Smart et al. and SeaZip, these figures give an idea of the required time of a CTO.

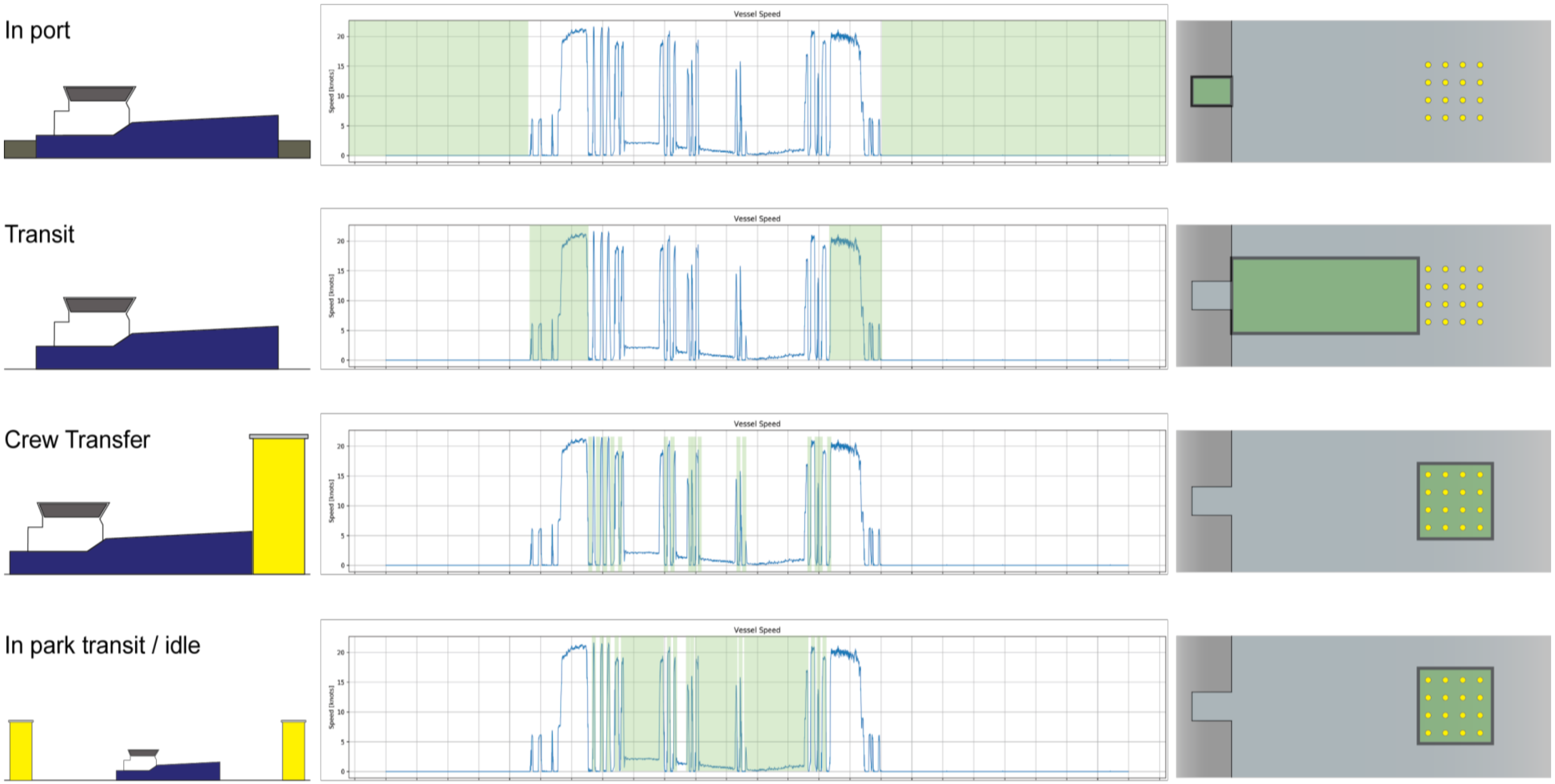

Figure 12: Crew Transfer Operation process steps Used data from MSG AIS Data Store. Own composition.

3.4.2 Weather window

The weather window for CTOs is severely restricted by the sea state, and in particular by the mean significant wave height (ECN, 2016; Dalgic, et al., 2015a; SPARTA, 2017). As mentioned, the maximum Hs in which CTO can be executed safely with CTVs is around 1.5 - 1.8 m. According to Damen and Smart et al. (2016) CTOs can be executed in higher Hs, however, for safety reasons this is only done when there is no other option (e.g. when technicians must be picked-up from a turbine). Some wind farms – such as the Alpha Ventus project in Germany – even forbid CTOs to be executed with CTVs when the Hs is above 1.5 m (4C Offshore, 2016). CTOs are sometimes postponed although the Hs is below 1.5 m, states SeaZip, as certain weather conditions makes it unsafe to execute CTOs. Moreover, crew and technicians can become seasick when sailing in severe sea states with relatively small CTVs, which has a major impact on their performance (ECN, 2016).

Other weather related limiting factors are wind speed and visibility. To start with the wind speed; according to ECN (2016) the maximum wind speed in which a large CTV can operate is 15 m/s, which is around 7 Beaufort. As can be seen in Figure 13, the Hs is in all cases the limiting factor before wind speed. Therefore, in practice the wind speed constraint is negligible for these three wind farms (and perhaps all wind farms). The visibility factor is less strict, as according to 4C Offshore (2016) daylight during CTOs is preferred, but not strictly required. About other conditions causing limited visibility such as fog is little known and there are no data available, therefore, this is left out of the analysis.

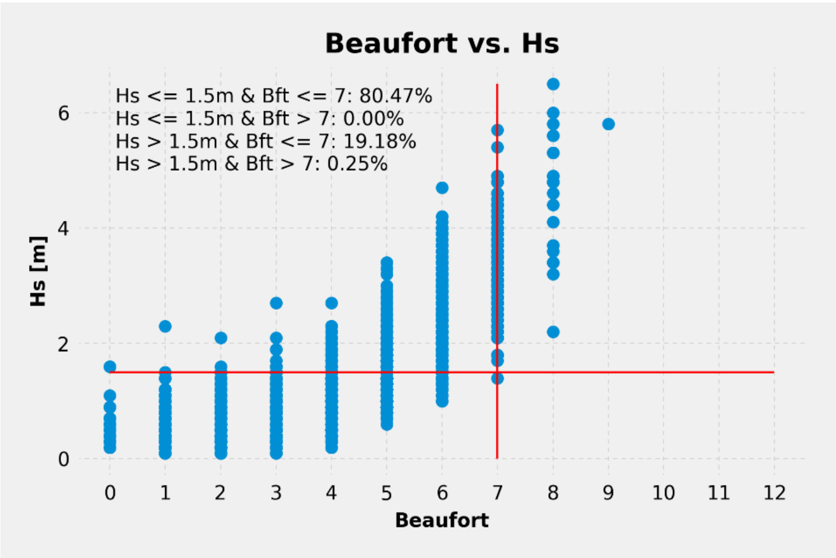

Figure 13: Beaufort vs. Hs. Data of Amrumbank, Thornton, and Lynn from April 2015 till April 2017. Used data from MSG AIS Data Store, figure is own composition.

Because the Hs is the main limiting factor for CTOs, the offshore wind industry has a high degree of seasonality. In general, winter months are characterised by harsher weather conditions than the summer months, resulting in low turbine accessibility during winters (4C Offshore, 2016; Dalgic, et al., 2015a; Tavner, 2012). Figure 14 illustrates the Hs in the Amrumbank, Thornton and Lynn wind farms over time, in which this seasonality is reflected.

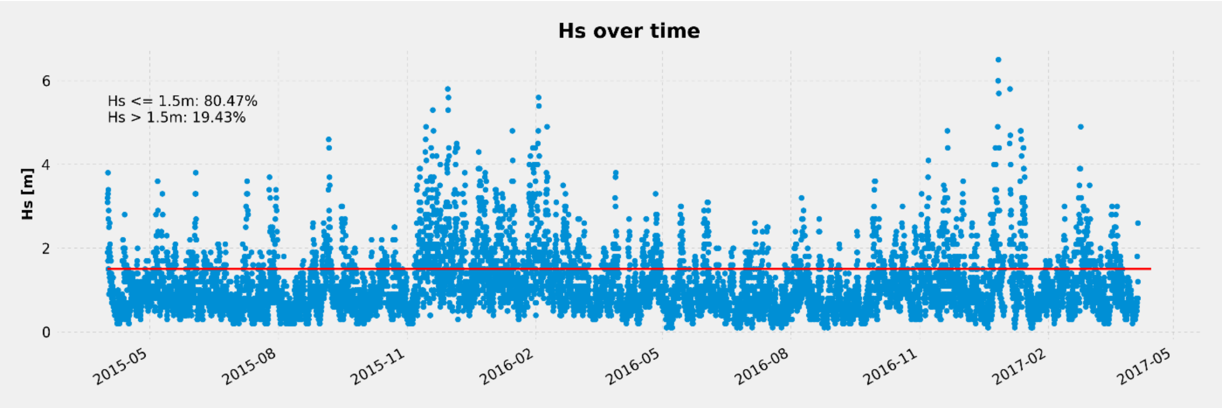

Figure 14: Hs over time. Data of Amrumbank, Thornton, and Lynn from April 2015 till April 2017. Used data from MSG AIS Data Store, figure is own composition.

According to Dalgic et al. (2015a) offshore wind farms are 200 days per year accessible. They do not state if this number is averaged/ what the variance is. Shafiee (2015b) is a bit more optimistic stating that offshore wind farms can be accessed 60% to 70% of the time, which equals 220 to 255 days per year. Turbine access is off course strongly dependent on weather conditions, wind farm location and used material. A negative effect on turbine accessibly is the trend that new wind farms tend to move away from the shore. However, this may be compensated by larger vessels and techniques such as heave compensated gangways.

Figure 15 illustrates the percentage of full-day access days of three wind farms as a function of CTVs' Hs constraint to safely execute CTOs. Thornton is for example fully accessible for ±83% of the days if the used CTVs are able to execute CTOs in Hs up to 2.0 m. A full-day access day is defined as a day for which the Hs is <= x meter during working hours (6am till 6pm). For this, the Hs in the weather forecasts of 6am, 12pm and 6pm should all be <= x meter, since the Hs is linearly interpolated between the forecasts as is explained in section 5.3. As can be seen, the accessibility for Hs = 1.5 m is between 61% and 87% for the shown wind farms in 2016, which is close to Shafiee's (2015b) claim. It seems that, especially for Amrumbank and Thornton, the number of access days can be significantly improved if transfers could be executed safely in Hs up to 2.0 m. Of course, these results are only for 3 wind farms over a relatively short time period. Nonetheless, due to their geographical location similar trends are expected for other wind farms. Furthermore, Figure 15 shows that (especially for Amrumbank and Thornton) the sea states where relatively calm in 2016. More graphs about turbine accessibility per wind farm are included in Appendix E.

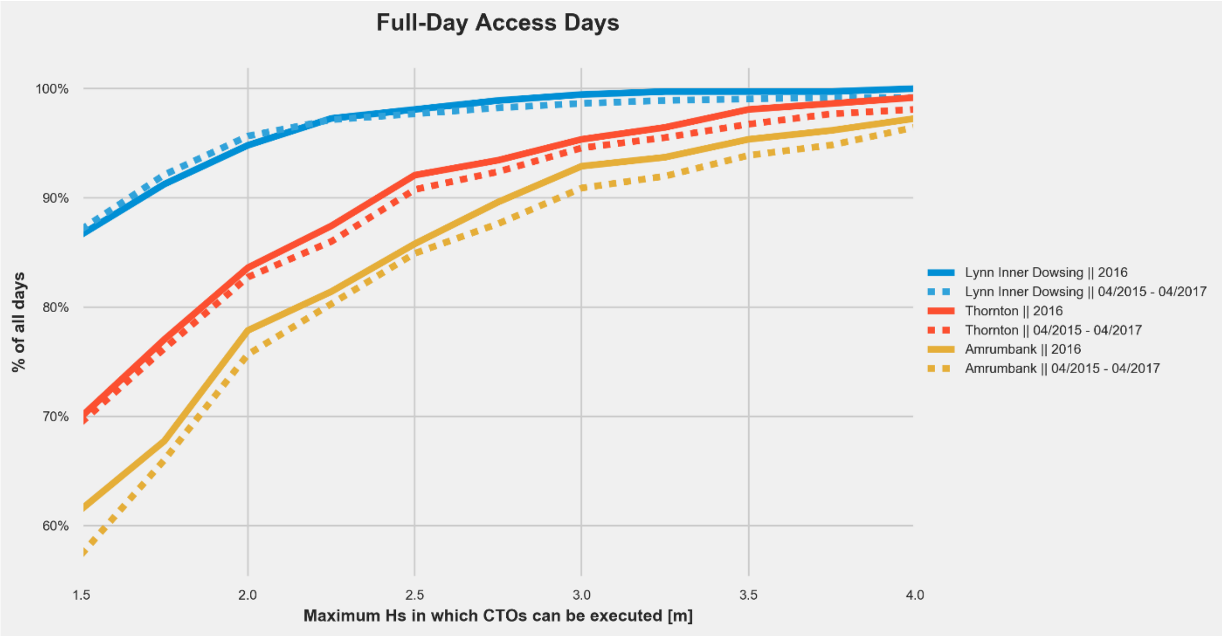

Figure 15: Turbine accessibility based on varying maximum Hs constraints. Used data from MSG AIS Data Store, figure is own composition.

3.5 Key Parameters & Key Performance Indicators of Crew Transfer Operations

Several factors determine the efficiency/ effectiveness of CTVs for CTOs, however, not all are relevant/ suitable for the data analysis of this project. The comfort of technicians, for example, cannot be quantified based on the available data. Factors that are suitable for the data analysis are discussed in this section.

3.5.1 Key parameters

The first KP to be discussed is CTVs' speed. Speed is of high importance for the efficiency of the vessel, states Mr Robert (Damen's Business Development and Market Intelligence Director). A high maximum speed results in less lost time for transits to, from and within wind farms. This is important for two reasons: transit time is detrimental to the in-field working time; and, expensive technicians cannot work during transits. So, sailing faster may result in less required wind farm visits per year and may spare an enormous number of man-hours. On the contrary, a higher maximum speed results evidently in higher fuel costs.

The second KP is the maximum Hs in which CTVs can safely execute CTOs. As explained in section 3.4.2, this KP is important for the wind farm accessibility that, in turn, is important to minimise downtime of turbines. Moreover, higher accessibility may mean that the peak demand for CTVs in the summer period could be evened out over more months, resulting in lower costs. This KP may be related to three aspects: vessel limits, human limits and regulations.

The limitations of CTVs are related to the physical possibilities to land a CTV on a turbine. It is not difficult to imagine that at a certain point e.g. the waves become too high to push the bow the turbine/ connect a gangway. This tipping point, however, is dependent on among others the hull shape, vessel length and the presence of equipment such as a heave compensated gangway.

Apart from vessel limits, also human limits play a role in this KP. Vessel motions could cause seasickness, which is detrimental to the workability of technicians (Colwell, 2005; Bos & Houben, 2013). The Carbon Trust (2017) conducted a research into the weather window of CTVs based on the maximum acceptable accelerations and motion limits for three reference catamarans with lengths of 18 m, 22 m and 26 m. Based on their results, it can be concluded that the maximum Hs for transfers is for most wave directions and periods (far) below 2.0 m. Furthermore, they state that the maximum acceptable speed during transits drops significantly when the Hs increases.

Aforementioned, some wind farms prohibit CTOs to be executed in Hs higher than 1.5 m. This may influence the results of the data analysis in such a manner that the KP may be 1.5 m Hs regardless of CTVs' seakeeping performance.

3.5.2 Key performance indicators

This project primarily focuses on crew transfers executed with CTVs. Therefore, the number of executed transfers per a given time unit is an indicator for CTV performance. This KPI is necessary to model CTV demand, however, there are some points that may make that this KPI has a great variance. In the following, two of these points are highlighted.

First, the number of executed crew transfers per time unit depends on the task of the turbine technicians. The time between drop-off and pick-up of technicians can for example be much shorter if the technicians conduct a manual reset in comparison to a major repair job.

Secondly, the number of technicians that can be accommodated have a major effect on the number of crew transfer that can be executed on a working day. Industry standard is a capacity of 12 technicians as is explained in section 3.2.3. However, currently CTVs with a higher capacity are being used. If more technicians can be transported, more transfers can be executed and the idle time in the wind farm will decrease. However, technicians are waiting longer on-board before they can be transferred, which costs money. By analysing data of a large number of crew transfers, a distribution of the executed CTOs per hour is composed.

Chapters one until three formed the business understanding step of the CRISP-DM model. In these chapters, the project is introduced and the demand and supply side of crew transfers is discussed. The KPs and KPIs presented at the end of chapter two and three are important input for the CTV Demand Model.

The next step of the CRISP-DM model is data understanding and preparation. In the next chapter, the wind farms that will be used for the project are selected. This step is needed to scope the project and to determine from which CTVs the AIS data should be required.

4 Wind Farm Selection

This chapter describes the selection process of the wind farms for the analysis, and the reasoning behind this. Three wind farms are selected, two for the first analysis and one to extend the project. Furthermore, a list with potential wind farms for further extension is presented.

4.1 Wind Farm Selection Algorithm

The wind farms are selected via the underneath algorithm. This algorithm is developed by: first, inventory of the wind farm requirements of Damen, MSG and the project scope; and second, critically determining the constraining steps necessary to eliminate all non-suitable wind farms. The algorithm is applied and explained in the remainder of this chapter.

1. Select suitable wind farms based on location and lifecycle phase;
2. list all Damen FCS 2610 vessels including charter contracts;
3. find overlap between step 1 and step 2, i.e. find Damen FCS 2610 vessels that have/ had a contract to service one of the selected wind farms;
4. MSG verifies if the terrestrial AIS coverage for the remaining wind farms after step 3 is sufficient. If so, the wind farm is selected.

4.2 Suitable Wind Farms

To scope the project, only a selection of wind farms located in the North Sea is included in the analysis. Furthermore, the selected wind farms should have sufficient terrestrial AIS coverage to ensure comprehensive AIS datasets. According to MSG, the coverage is generally sufficient for wind farms within approximately 25 nautical miles (nm) (±46.3 km) from the shore, however, this should be checked per case. AIS makes uses of Very High Frequency radio waves, which has a transmission range that is approximately its line of sight. This means that one can increase the so-called radio horizon by placing the AIS antenna and receivers at height. Since CTVs are relatively small vessels, the AIS antennas are placed relatively low. This influences the terrestrial AIS coverage of these vessels significantly. Moreover, the density of AIS receivers, weather conditions and large objects may influence the coverage.

According to a database from 4C Offshore (2017c), the 27 windfarms listed in Table 5 are all fully commissioned wind farms, located in the North Sea, within 25 nm from the shore and are non-demo/ test sites. These wind farms are the first pool to select from (the terrestrial AIS coverage is not yet verified in this stage).

Table 5: Suitable wind farms. Data from 4C Offshore (2017c), table is own composition.

Wind farm	Country	Power Generating date	# turbines	Turbine type and manufacturer	Distance to shore [km]
Amrumbank West	Germany	22-Oct-15	80	SWT-3.6-120 (Siemens)	44
Belwind	Belgium	9-Dec-10	55	V90-3.0 MW Offshore (Vestas)	44
Butendiek	Germany	4-Aug-15	80	SWT-3.6-120 (Siemens)	35
Egmond aan Zee	Netherlands	2007	36	V90-3.0 MW Offshore (Vestas)	13
Eneco Luchterduinen	Netherlands	21-Sep-15	43	V112-3.0 MW Offshore (Vestas)	24
Greater Gabbard	United Kingdom	7-Aug-13	140	SWT-3.6-107 (Siemens)	32
Gunfleet Sands	United Kingdom	10-Jun-10	48	SWT-3.6-107 (Siemens)	7
Horns Rev 1	Denmark	11-Dec-02	80	V80-2.0 MW (Vestas)	17
Horns Rev 2	Denmark	31-Jan-10	91	SWT-2.3-93 (Siemens)	32
Humber Gateway	United Kingdom	31-Mar-15	73	V112-3.0 MW Offshore (Vestas)	10
Inner Dowsing	United Kingdom	Mar-09	27	SWT-3.6-107 (Siemens)	6
Kentish Flats	United Kingdom	Dec-05	30	V90-3.0 MW Offshore (Vestas)	9
Kentish Flats Extension	United Kingdom	2-Dec-15	15	V112-3.3 MW Offshore (Vestas)	8
Lincs	United Kingdom	27-Sep-13	75	SWT-3.6-120 (Siemens)	9
London Array	United Kingdom	6-Apr-13	175	SWT-3.6-120 (Siemens)	27
Lynn	United Kingdom	Mar-09	27	SWT-3.6-107 (Siemens)	6

Northwind	Belgium	30-Jun-14	72	V112-3.0 MW Offshore (Vestas)	36
Prinses Amaliawindpark	Netherlands	24-Jul-08	60	V80-2.0 MW (Vestas)	26
Riffgat	Germany	7-Mar-14	30	SWT-3.6-120 (Siemens)	42
Scroby Sands	United Kingdom	14-Dec-04	30	V80-2.0 MW (Vestas)	3
Sheringham Shoal	United Kingdom	19-Apr-13	88	SWT-3.6-107 (Siemens)	21
Teesside	United Kingdom	16-Apr-14	27	SWT-2.3-93 (Siemens)	1
Thanet	United Kingdom	23-Sep-10	100	V90-3.0 MW Offshore (Vestas)	17
Thornton Bank phase I	Belgium	10-May-09	6	5M (Senvion)	27
Thornton Bank phase II	Belgium	31-Jan-13	30	6.2M126 (Senvion)	28
Thornton Bank phase III	Belgium	18-Sep-13	18	6.2M126 (Senvion)	28
Westermost Rough	United Kingdom	26-May-15	35	SWT-6.0-154 (Siemens)	11

4.3 Damen FCS 2610 Contracts & Wind Farm Overlap

The Damen FCS 2610 is specially designed for CTOs in the offshore wind industry. For Damen, it is therefore interesting to include one or more of these vessels in this project. Therefore, a constraint for selecting wind farms for the first analysis is that a Damen FCS 2610 has/ had a contract to service the wind farm. A database from 4C Offshore (2017b) is used to find all Damen FCS 2610 vessels and their corresponding charter contracts. From this list, all non-North Sea contracts and all contract days before the power generation date of the wind farms are removed. This results in a list with all contract days for fully commissioned wind farms in the North Sea assigned to Damen FCS 2610 vessels (see Table 6). (A contract day is defined as a calendar day for which a CTV was under contract.)

Table 6: Damen FCS 2610 North Sea Contracts. Data from 4C Offshore (2017b), table is own composition.

Wind farm	Vessel Name	Start Contract	End Contract	Length Contract in days	Contract Days per Wind Farm
Amrumbank West	MCS Pampero	22-Oct-15	6-Nov-15	15	687
	MCS Taku CPP	11-Mar-17	20-Apr-17	40	
	MCS Taku CPP	22-Oct-15	7-Nov-15	16	
	MV Carrier	22-Oct-15	15-Apr-17	541	
	SeaZip 5	19-Jul-16	23-Jul-16	4	
	SeaZip 5	15-Aug-16	1-Sep-16	17	
	SeaZip 5	21-Apr-16	14-Jun-16	54	
Belwind	MCS Taku CPP	26-Nov-16	10-Dec-16	14	14
Butendiek	Sure Swift	4-Aug-15	23-Sep-15	50	54
	Sure Swift	13-Dec-15	17-Dec-15	4	
Eneco Luchterduinen	Njord Alpha	27-May-16	28-May-16	1	1
Greater Gabbard	MCS Coromell	24-Oct-13	3-Dec-13	40	40
Gunfleet Sands	Marineco Thunderbird	1-Mar-14	5-Apr-14	35	35
Inner Dowsing	Marineco Thunderbird	3-Jun-13	17-Dec-13	197	202
	Rix Lion	20-Jul-14	25-Jul-14	5	
Lincs	Rix Lion	13-Sep-14	29-Sep-14	16	16
London Array	MCS Coromell	5-Jan-14	27-Jan-14	22	22
Lynn	Marineco Thunderbird	3-Jun-13	17-Dec-13	197	202
	Rix Lion	20-Jul-14	25-Jul-14	5	
Prinses Amaliawindpark	Njord Alpha	12-May-16	18-May-16	6	6
Thornton Bank phase I	Aquata	1-Dec-12	10-Dec-16	1470	2443
	Arista	1-Dec-12	30-Jun-15	941	
	Arista	30-Sep-16	1-Nov-16	32	
Thornton Bank phase II	Arista	19-Dec-16	4-Mar-17	75	334
	Marineco Stingray	15-Oct-16	15-May-17	212	
	MCS Sirocco	14-Jul-16	5-Aug-16	22	
	SeaZip 4	21-Mar-17	15-Apr-17	25	

4.4 Selected Wind Farms

Table 7 is derived from Table 6, and shows the Damen FCS 2610 vessels with the longest contract lengths. Long contract periods are preferred because this makes it possible to analyse a vessel in one wind farm over a longer time period. Especially contracts that last for 1 year and over are interesting because they include all four seasons. As can be seen, only 2013, 2014, and 2016 includes contracts that last for a full year. Since 2016 is the most recent, this year is the chosen timespan for the first analysis.

Table 7: Damen FCS 2610 contract periods interesting for analysis. Data from 4C Offshore (2017b), table is own composition.

Vessel Name	MMSI Number	Wind farm	Start Contract	End Contract	Length Contract in days
Aquata	253415000	Thornton Bank phase I	1-Dec-12	10-Dec-16	1470
Arista	253465000	Thornton Bank phase I	1-Dec-12	30-Jun-15	941
MV Carrier	219018788	Amrumbank West	22-Oct-15	15-Apr-17	541
Marineco Stingray	235103595	Thornton Bank phase II	15-Oct-16	15-May-17	212
Marineco Thunderbird	235092583	Inner Dowsing & Lynn	3-Jun-13	17-Dec-13	197

In 2016, the ‘Aquata’ had a contract for almost the whole year in Thornton phase I and the ‘MV Carrier’ had a full year contract in Amrumbank West (Amrumbank). Therefore, these wind farms are selected for the first analysis. None of the Damen FCS 2610 vessels had in 2016 a contract in the Inner Dowsing or Lynn. However, it is decided to select these wind farms to extend the project after the Amrumbank and Thornton analysis. Since the Thornton Bank Phase I, II and III are intertwined, they are considered as one wind farm (Thornton) for this project. The same applies to Lynn, Inner Dowsing and Lincs (Lynn Inner Dowsing).

According to MSG the terrestrial AIS coverage of Amrumbank, Lynn Inner Dowsing and Thornton is sufficient. This can be seen in the heat maps of these wind farms in Figure 16, where AIS data points are represented by black, red and yellow dots. Red and yellow means that the number of AIS reports corresponding to those locations is extremely high. It is remarkable that wind farms and turbine locations are easily noticeable on these heat maps.

Although the terrestrial AIS coverage of these wind farms is sufficient, it is not guaranteed that all AIS reports transmitted by the CTVs are received by the antennas on land for the reasons explained earlier in this chapter. To get an idea of the magnitude of the missing data the time interval between the AIS reports is analysed in section 5.2.3 and in Appendix F.

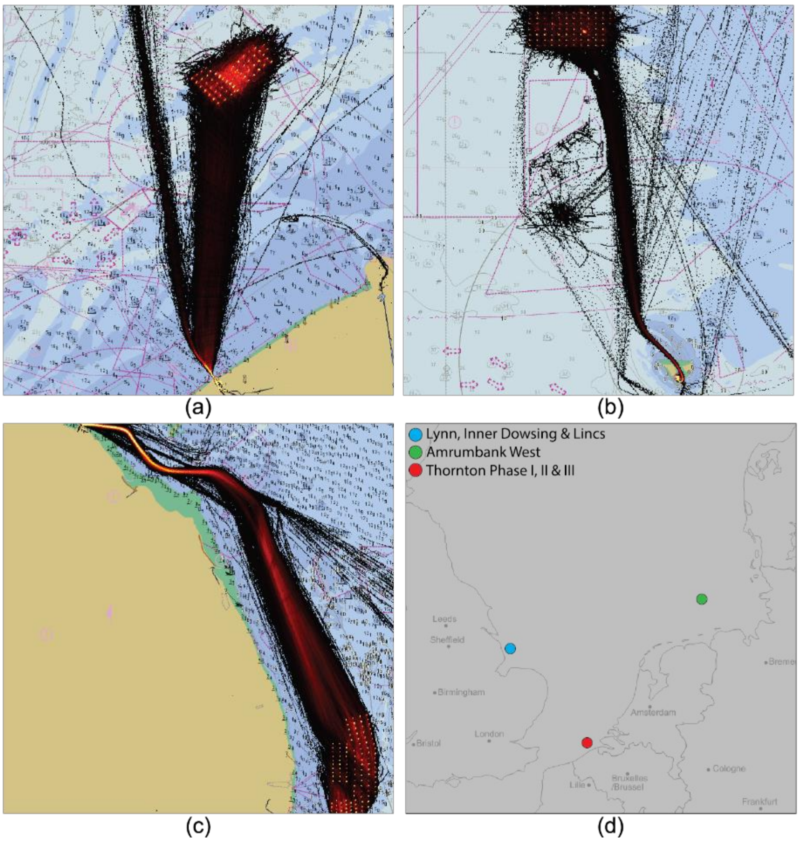

Figure 16: Heat maps of workboats between 15 and 55 meters over the course of 2016. (a) Thornton, (b) Amrumbank West, (c) Lynn, Lincs and Inner Dowsing. Figures composed in MSG Plotter.

The specifications of the selected wind farms are included in Appendix B. Other wind farms may be added in a later stadium of the project. If this would be the case, these wind farms will be selected from the wind farms included in Table 6 or via a similar procedure wherein the Damen FCS 2610 constraint is eased to all CTVs.

Three wind farms are selected in this chapter for the data analysis. In the next two chapters, the required data of these wind farms and the vessel working in these wind farms are collected, prepared and processed.

5 Collect & Prepare Data

There are three types of data required for this project: AIS, wind and sea state and wind farm/ turbine location. The collection and preparation of these datasets is discussed in this chapter, but first, the used applications from MSG for this purpose are introduced.

5.1 Used Made Smart Group Applications

MSG applications referenced and used for purpose of collecting and analysing the big data in this thesis are:

- **MSG AIS Data Store:** a database application which continuously absorbs worldwide AIS data and that currently covers > 80 TB of raw AIS data going back to 2005. The database also maintains global weather and sea state data as of 2012. It is the largest and most complete AIS database in the world.
- **MSG Prospector:** a smart portal to access the MSG AIS Data Store, with tools to filter any query amongst others on Maritime Mobile Service Identity (MMSI) number, vessel type, vessel length, time period and area. The application allows for quick visualisation and export of data reports in several formats.
- **MSG Plotter:** an easy to use, web browser based, chart plotter. Access to 14.500 ENC's (nautical charts), import functions for AIS data (also automatic from MSG Prospector) and a powerful toolset to plot tracks, objects or areas of interest, and animate vessel movements.

5.2 Automatic Identification System Data

5.2.1 Selecting and collecting Automatic Identification System data

The AIS data is selected and collected via two parallel processes of which the results are compared afterwards. Part A is purely based on market intelligence and Part B is an algorithm to identify CTVs based on AIS data. To verify the correctness of Part B, the outcome is compared with the results from Part A.

Part A:

A database from 4C Offshore (2017b) contains a list of all CTV charter contracts of which they are acquainted. This list is used to collect all MMSI numbers of the CTVs that were under contract in one of the selected wind farms over the course of 2016 (see Table 38 in Appendix C). The MMSI numbers are used to collect the AIS data from the MSG AIS Data Store.

Part B:

1. Use MSG Prospector to get the MMSI numbers of all vessel that:
    a. have sailed in the wind farm area of interest between 01 Jan 2016 00:00 UTC and 01 Jan 2017 00:00 UTC; and
    b. are between 15 and 55 meters. This to ensure that larger vessels used in the offshore wind industry such as jack-up vessels and SOVs are not selected.
2. Analyse vessel movements in MSG Plotter. Typical CTV movements/ patterns are selected by hand. This step is required to eliminate e.g. fishing vessels that trespassed the wind farm area.
3. Collect AIS data of the selected CTVs from the MSG AIS Data Store.

In 11 cases a CTV is not selected in Part B, despite the fact that it was under contract in one of the selected wind farms according to the results of Part A. It is verified based on AIS data that these 11 CTVs operated in one of the selected wind farms over the course of 2016.

In 10 cases these vessels are presumably erroneously deselected by hand in step B.2 due to short contract periods. These short contracts are difficult to detect when analysing a complete year by hand. It may be possible to improve this with machine learning techniques, whereby the computer learns to recognize when a movement/ pattern is typical for a CTV. Unfortunately, machine learning is beyond the scope of this project. In one case, the CTV length was 14m and therefore not selected in step B.1 due to the 15m constraint.

In 4 cases a CTV selected in Part B was not on the list from Part A. This illustrates that the information obtained from AIS data can be complementary to contemporary market intelligence as well. Furthermore, it is known based on AIS data that the registered contract lengths of 4C Offshore do not always correspond to periods on which the vessels visited the wind farm.

5.2.2 Remove outliers

Cleaning data is an important step of data analysis, since outliers may negatively affect the results. MSG already put a great deal of effort in data cleaning, nonetheless, the used data still contains a few outliers. These outliers are removed from the dataset, which is the most straightforward method for dealing with outliers.

5.2.2.1 Speed over ground

The AIS data include some clear outliers when it comes to the Speed over Ground (SOG) as can be seen in Figure 17 (a). The shown data is from a Damen FCS 2610 with a maximum speed of 25 kts. The data points above 50 kts are clearly outliers, however, for other points it is less clear if they are an outlier or not. To clean the data, all AIS position reports with a SOG higher than the maximum vessel speed plus 15% are considered to be outliers, and therefore removed from the dataset (see Figure 17 (b)). The reasoning behind this is discussed in the following.

Over more than 2 years of data, the maximum sea current in the selected wind farms was 0.6 m/s. Of course, this time period is too short to draw conclusions about the maximum current in these areas, but it gives an idea of the magnitude. Assuming that the current will not exceed 1.0 m/s (barring some extremes), the influence of the current on the SOG will not exceed 2 kts (=1.03 m/s). When adding 1 kts for wind influences and wave surfing, the maximum added speed on top of the maximum vessel speed is around 3 kts. The Damen FCS 2610 has a maximum speed of 25 kts plus 3 kts for corrections equals a maximum SOG of 28 kts. This is approximately the maximum vessel speed plus 15%. This rule of thumb is verified by Kees Van Oosten, a Development Engineer from Damen's R&D department. According to him, a SOG above 28 kts is unlikely for a Damen FCS 2610, especially since the maximum vessel speed is only met when the vessel is unloaded and weather and sea conditions are calm.

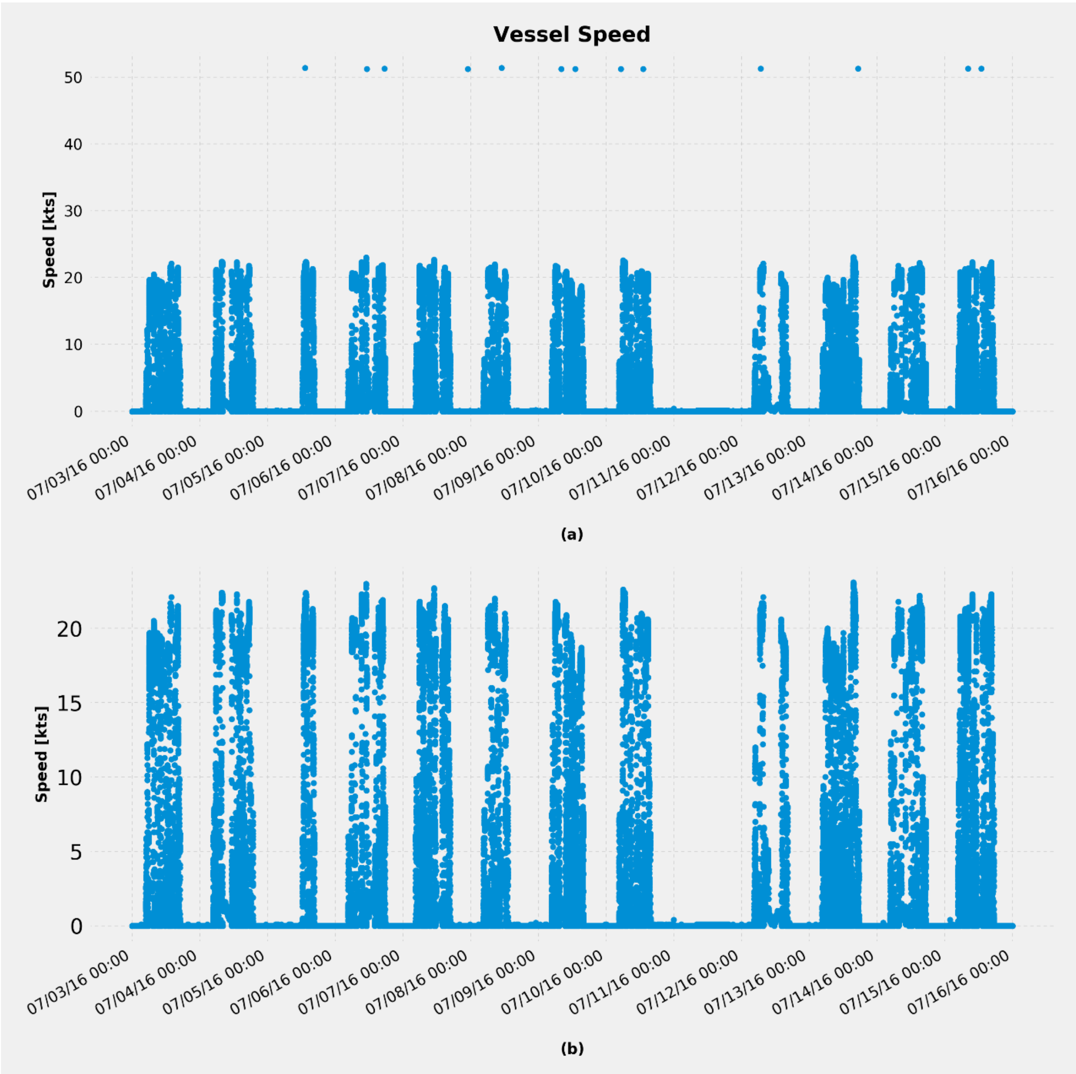

Figure 17: Speed over ground of a Damen FCS 2610 with (a) and without (b) outliers. Used data from MSG AIS Data Store, figure is own composition.

5.2.2.2 Position jumps

A position jump is a fault in the data whereby the location of an AIS report is not logical/ or physically possible in respect to the location of the prior and subsequent AIS reports. Position jumps happen in less than a few seconds, and are mostly caused by reflections of the GPS signal on large objects such as wind turbines and cargo cranes. Water inside the GPS antenna is also a common cause of position jumps.

The red dots in Figure 18 (a) and (b) illustrate position jumps. It is not hard to see that the CTV physically could not have sailed from the green dots to the red dot and back within a few second. Moreover, it is remarkable that the vessel jumps multiple times to the same location.

During crew transfers position jumps could disturb the analysis as is depicted in Table 8. Due to the position jump in row 6 the transfer is counted double. The obtained data from MSG is already cleaned from most position jumps, and therefore this is not expected to form a significant problem for the analysis. Moreover, the used algorithm is designed to deal with these kind of outliers as will be explained in section 6.1.1.

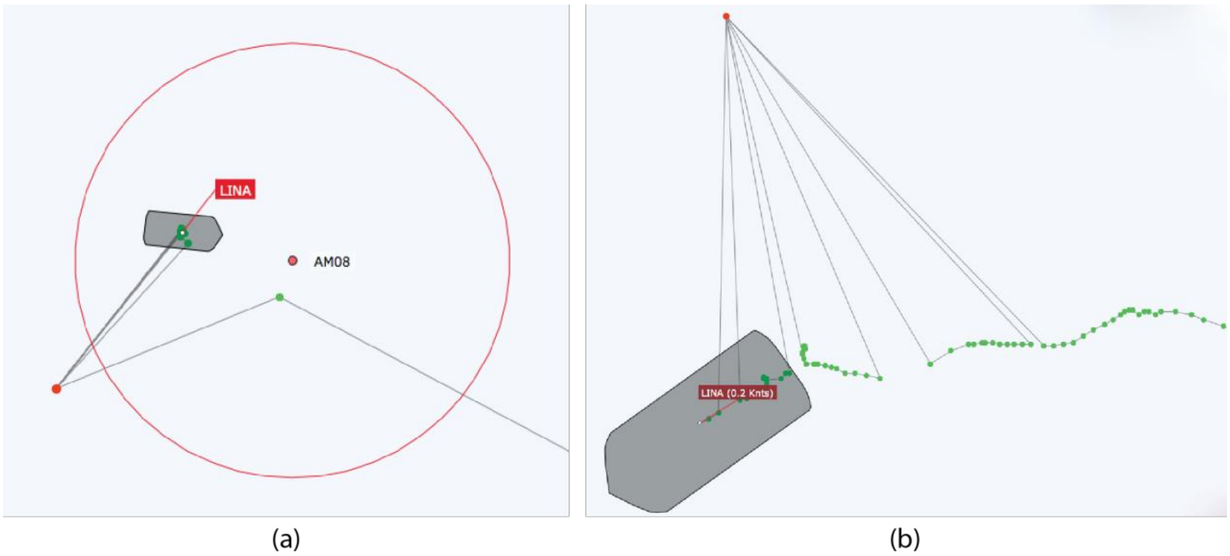

Figure 18: Position jumps. Figures composed in MSG Plotter.

Table 8: Corresponding data of position jump of Figure 18 (a).

	Date and UTC Time	MMSI	Lat	Lon	SOG	wt_id	transfer_time
1	5/7/2016 6:20:46	219019775	54.537803	7.732077	12.2		
2	5/7/2016 6:21:46	219019775	54.53877	7.728948	0.3	AM8	00:02:33
3	5/7/2016 6:22:27	219019775	54.53877	7.72895	0.1	AM8	
4	5/7/2016 6:22:56	219019775	54.538773	7.72895	0	AM8	
5	5/7/2016 6:24:06	219019775	54.538782	7.728955	0	AM8	
6	5/7/2016 6:24:19	219019775	54.322999	7.436998	0		
7	5/7/2016 6:25:15	219019775	54.538783	7.72896	0	AM8	00:19:22
8	5/7/2016 6:26:46	219019775	54.538787	7.728955	0	AM8	

5.2.3 Data gaps

A threat of AIS based analysis is the fact that it is not known whether the collected data is complete, and one cannot include vessels/ time periods for which there is no data available. Missing data could be caused by the following reasons. First of all, some CTVs may not be selected by hand in the algorithm described in section 5.2.1. However, MSG expects – based on their expertise – that most CTVs that were operative in the wind farms are selected. Secondly, some CTVs may not have an AIS transmitter/ turned off the AIS transmitter since they are not obliged to fit a transmitter as is explained in section 3.2.3. Thirdly, the dataset contains some gaps over time. Large gaps of e.g. a day are relatively easy to notice. Smaller gaps however, are harder to detect. Fortunate, smaller gaps are less detrimental to the analysis since the probability that e.g. a transfer is missed becomes smaller when the gap becomes smaller. The number and length of the gaps can be found by analysing the time delta between consecutive AIS reports.

As can be seen in Figure 19, more than 95% of the time deltas of the in-field data is shorter than 4 minutes (barring one CTV). Evidently, the probability of missing a CTO is directly correlated to the frequency and length of time deltas. So, for Thornton there is a realistic probability that some CTOs are missed (this is in fact known from analysing CTV movements in MGS Plotter). For Amrumbank and Lynn Inner Dowsing is the probability of missing CTOs smaller, since 95% of the time deltas for these wind farms are respectively less than 3 and 2 minutes (see the CDFs in Appendix F).

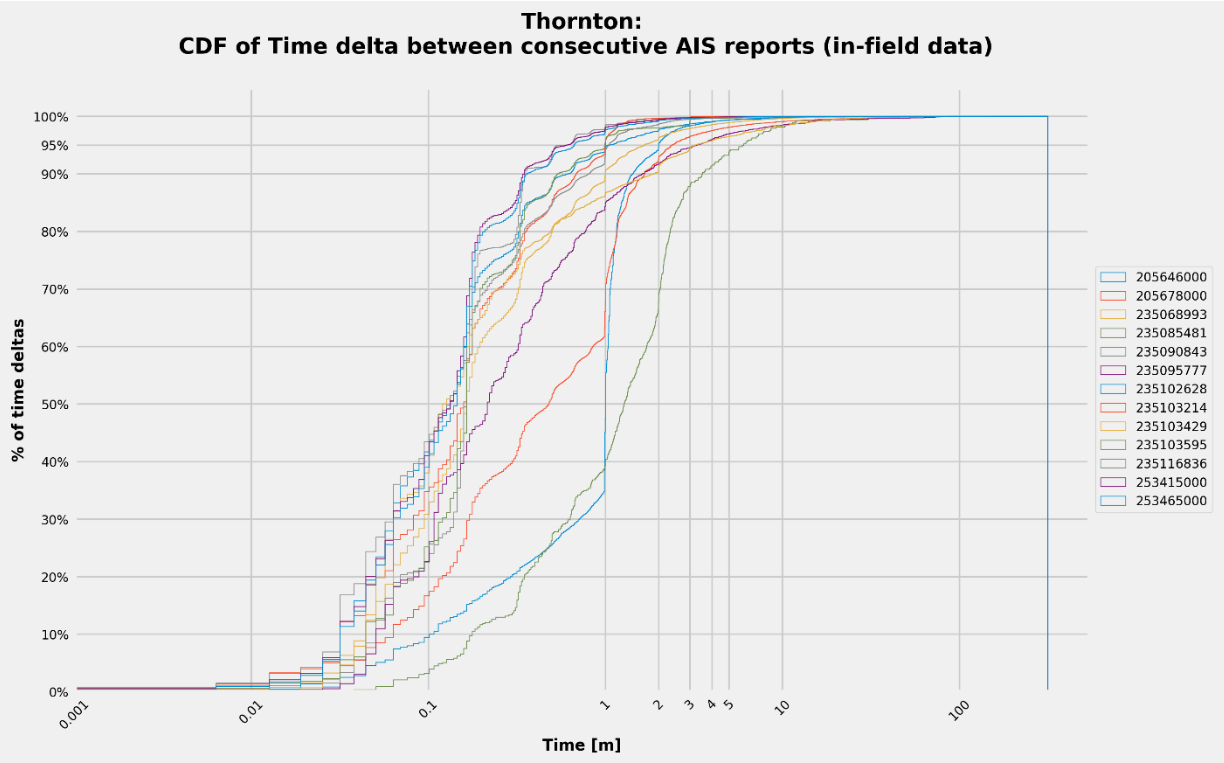

Figure 19: Cumulative Distribution Function of time deltas of in-field AIS data of all CTVs operative in Thornton in 2016. Used data from MSG AIS Data Store, figure is own composition.

The time spent in the wind farm per time delta category is illustrated in Figure 20. Time deltas >= 120 minutes are cut to 120 minutes because the CTVs may have left the wind farm or have turned off their AIS transponder.

A potential method to handle the data gaps is to assume that the CTV's behaviour remained unchanged during the data gaps. Based on this assumption, the number of executed crew transfers can be scaled based on the ratio of time passed during gaps to time passed during non-gaps. On the contrary, the data gaps may have been caused because of the CTV's behaviour changed. MSG states that data gaps can be caused by many reasons, of which purposely turning of the AIS transponder is not an unlikely cause. Especially because the terrestrial AIS coverage is considered to be sufficient for the operational area of the CTVs.

Although the total time over the time deltas >= 5 minutes is significant for some vessel, it is decided not to scale the number of CTOs since the cause of the time deltas is unambiguous. Moreover, the obtained results from the data mining algorithms are considered to be fit for purpose.

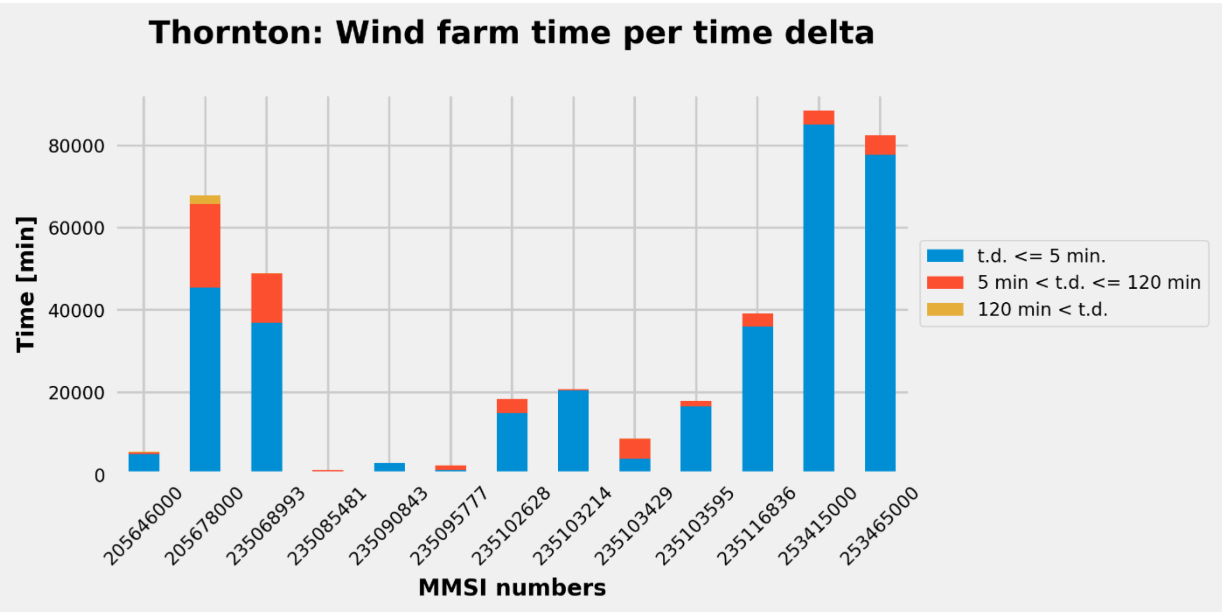

Figure 20: Distribution of wind farm time per time delta category in Thornton. Source: own composition.

5.3 Wind & Sea State

The wind and sea state data is obtained via the MSG AIS Data Store and is from the widely recognised European Centre for Medium-Range Weather Forecasts (ECMWF) and National Oceanic and Atmospheric Administration (NOAA). The ECMWF and NOAA release weather forecasts every 12 hours, combined this results in one forecast per 6 hour. By interpolating between data locations, MSG provides accurate weather and sea state data per ¼ latitude degree * ¼ longitude degree area. The used data is from the centre of each wind farm. An example of the raw data is depicted in Table 9. This data is prepared and merged to the AIS data via the following three steps:

1. the non-highlighted columns of Table 9 are deleted because they are assumed to be irrelevant for this project;
2. the data is linearly interpolated to get a dataset with values per minute instead of per 6 hours. According to MSG, this is the most efficient, accurate and workable approximation of the wind and sea states between forecasts; and
3. the wind and sea state data is merged to the AIS data based on date-time. For the merging, the AIS date-time is rounded to minutes, e.g. an AIS report with a date-time of 1/1/16 8:10:11 is merged to the wind and sea state report with a date-time of 1/1/16 8:10.

Table 9: Wind and sea state data for Thornton wind farm from MSG AIS Data Store.

Date and Time	Pressure (hPa)	Temperature (Â°C)	Current (m/s)	Current Direction (m/s)	Wind (Bft)	Wind Direction (Bft)	Precipitation (mm/6hr)	TotalWavesHeight (m)
4/1/15 0:00:00	1014.7	6.8	0.3	59.3	7	104	0	3.1
4/1/15 6:00:00	1018.5	6			7	110	0	3.3
4/1/15 12:00:00	1021.9	8.3			6	100.2	0	2.7

Continued:

TotalWavesDirection (Â°)	TotalWavesPeriod (s)	SwellWavesHeight (m)	SwellWavesDirection (Â°)	SwellWavesPeriod (s)	IceConcentration (%)	CloudCover (%)	SeaSurfaceTemperature (Â°C)	IceThickness (m)
111	6.4	0.7	163.6	8.4		1	7.4	
114	6.5	0.8	158.8	8.6		5		
109.3	6.1	1	164.6	8.4		20		

5.4 Wind Farm & Turbine Location

Geographical information from the wind farm and turbines is necessary to determine whether a CTV is executing CTOs. This section elaborates on how this information is collected.

5.4.1 Wind farm polygon

For this project, it should be known when a CTV is within a wind farm. MSG Plotter is used to get the corner coordinates of the polygon that describes the wind farm area (see white area in Figure 21). Where possible, this polygon follows the lines on the nautical chart that demarcate the area around the turbines in which non-wind farm related vessels are not allowed to sail. These polygons are used to determine if a CTV is within the wind farm. The same method is used to define the port areas.

Figure 21: Example of the polygon that describes the Amrumbank wind farm area. Figure composed in MSG Plotter.

5.4.2 Turbine locations

The exact locations of wind turbines are not always marked on the nautical charts. Instead, the location of the corner turbines is marked, which are used to demarcate the wind farm area. For this project however, the location of each individual turbine is required. To obtain these locations, three different algorithms are tested. The first algorithm is selecting turbine locations by hand on an AIS data heat-map, the second algorithm makes use of the grid outlook of wind farms and the last algorithm is based on the DBSCAN method to automate the first algorithm.

Algorithm A:

1. Create a heat-map of the AIS data of CTVs operating in the wind farm of interest in MSG Plotter.
2. Select the turbine locations by hand on the heat-map, and collect their GPS coordinates. As is shown in Figure 16 in section 4.4, the turbines can be easily noticed on the heat-map since they are frequently visited by CTVs (yellow dots). These points are based on the AIS locations, and thus an approximation of the turbine locations.
3. Correct mistakes by hand in MSG Plotter. It is assumed that a turbine location is incorrect if it is not visited by a CTV over a long time period.

Algorithm A is time consuming and sensitive for mistakes since the turbine locations are set by hand. Nonetheless, the outcome is quite good for most turbines and only a few turbine locations had to be corrected.

Algorithm B:

1. Collect GPS coordinates of the corner turbines that are marked on nautical charts.
2. Use the grid outlook of the wind farm to estimate the location of all turbines based on the known GPS coordinates.

Algorithm B is very accurate for some wind farms such as Amrumbank that is built in a perfect grid outlook. The algorithm is not working, however, when a wind farm is not designed and/or built in a suitable grid outlook. Moreover, the coordinates of some turbines should be known for this method.

Algorithm C:

This algorithm is tested to automatically distract turbine locations from AIS data. The turbine locations are calculated with the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm. The DBSCAN can be used to make clusters of points (in this case AIS locations) that are densely packed, and classifies points without close-neighbours as outliers (Ester, et al., 1996).

The used input dataset for this algorithm are all AIS reports for which the CTVs are located in the wind farm area and have a SOG of 0.0 kts. For the working of the DBSCAN three parameters has to be set: number of AIS reports used; maximum distance between two points that can belong to the same cluster; and the minimum number of points needed to form a cluster. These parameters should be set and tested by hand for each wind farm to get accurate results, which is a very time consuming task. Furthermore, some outlier-clusters should be removed by hand (see point 81 in Figure 22).

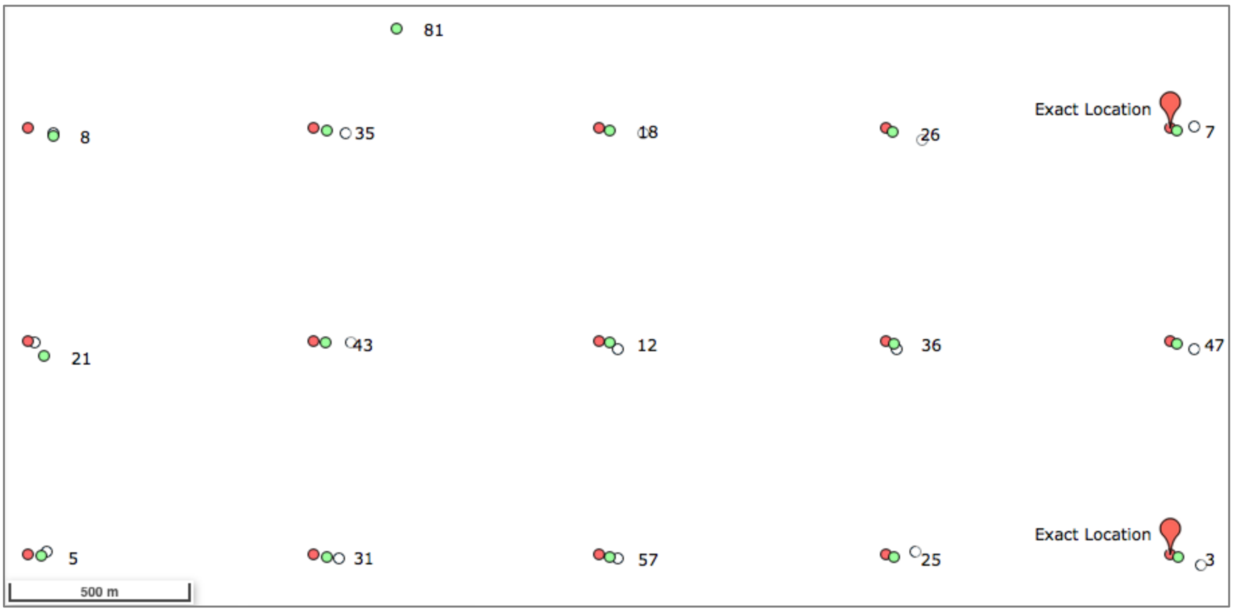

Figure 22: Results of the three algorithms for a part of Amrumbank West. (A = white, B = red, C = green). The results for all algorithms are similar. Only point 81 is an outlier from algorithm C. Figure composed in MSG Plotter.

The DBSCAN algorithm gives outstanding results for e.g. Thornton (see figure Figure 23). However, as can be seen in Figure 24 it does not work properly for other wind farms such as Lynn Inner Dowsing.

In the case of Lynn Inner Dowsing, this is probably caused by the density distribution of AIS reports within the wind farm. As can be seen in Figure 16 c in section 4.4, the density of AIS reports in the top and bottom part of the wind farm is denser than in the middle part. This makes it difficult to set the parameters by hand in such a manner that it works for both areas within the wind farm.

Nonetheless, the DBSCAN is an extremely convincing method to identify turbine locations. A special DBSCAN based algorithm should be developed for this case and other AIS based location identification applications to give the required results, however, this is outside the scope of this project.

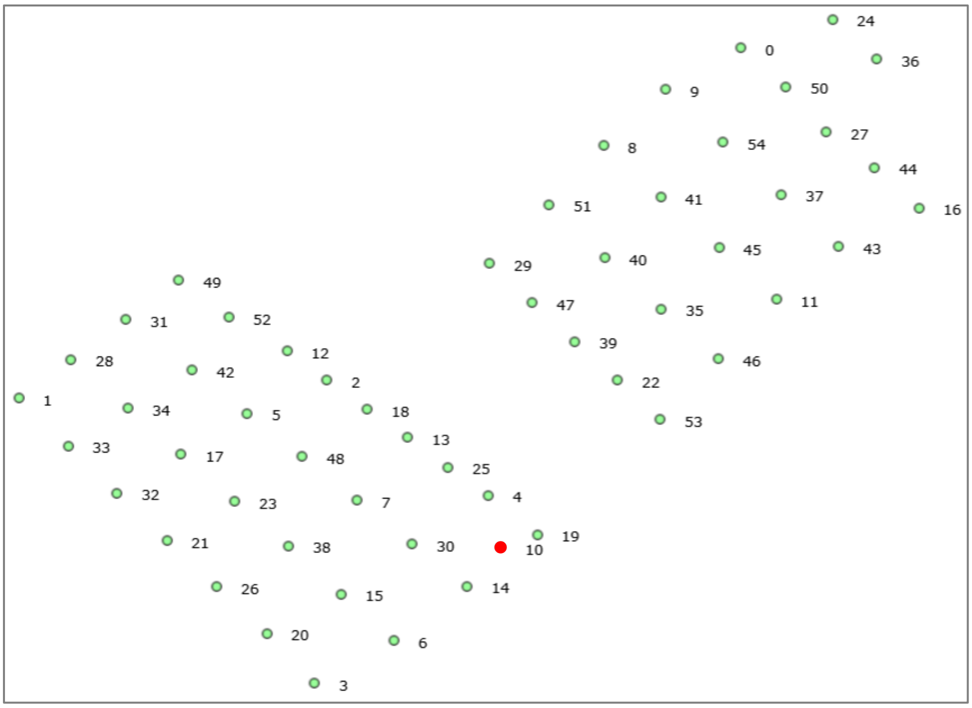

Figure 23: Results of the DBSCAN algorithm for Thornton. For this wind farm the algorithm results are workable. Only the red dot at number 10 is not a wind turbine. Figure composed in MSG Plotter.

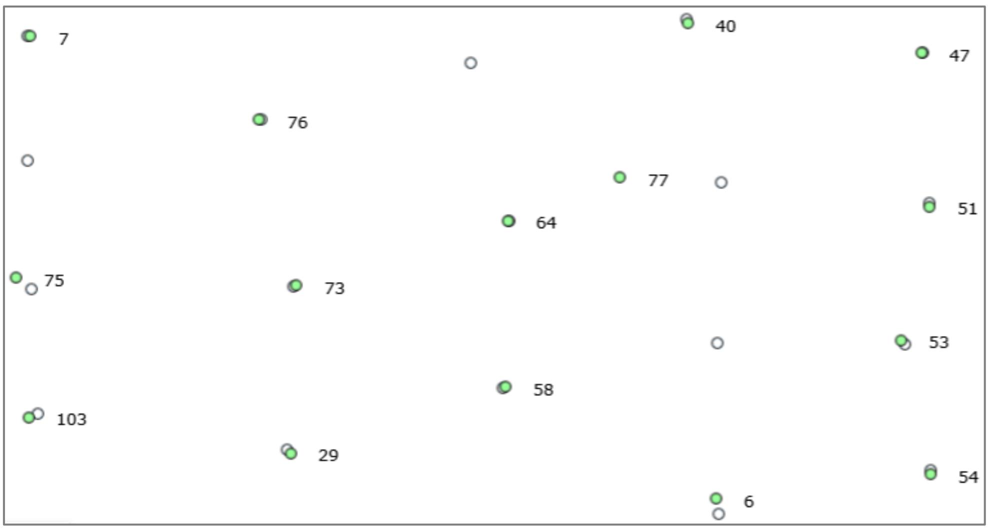

Figure 24: Results of algorithm A (white) and C (green) of a part of Lynn Inner Dowsing. Figure composed in MSG Plotter.

The used method to collect the turbine locations differ per wind farm. Algorithm A is used for Lynn Inner Dowsing. The results of this algorithm are excellent for Lynn Inner Dowsing. This is probably because the density of AIS reports for this wind farm is the highest of all three (see Appendix F), which results in a very accurate heat-map. The turbine locations of Amrumbank and Thornton are estimated with algorithm C. The DBSCAN method gives workable results for these two wind farms, although some outliers had to be removed. Algorithm B can be used for Amrumbank as well, however, the DBSCAN gives slightly better results. Furthermore, the grid outlook of the wind farms is used to identify outliers.

Alternatively, the GPS coordinates of the turbine locations could be bought from several providers. This may improve the outcome of the algorithm as will be described in section 6.1.2.2. However, a solely AIS based method is preferred and buying the information could become quite expensive when multiple wind farms are analysed.

This chapter discussed how the data is collected and prepared for the data analysis. This data in itself does not provide any information. Therefore, the next chapter is about the data mining algorithms used to translate the data into the required information.

6 Data Mining Algorithms

An important step of the CRISP-DM is processing/ modelling the data. This step is necessary to translate the datasets into the desired information (Shearer, 2000). For this project, multiple data mining algorithms are developed to translate the AIS, sea state and wind farm data into the required information to model CTV demand. The first discussed algorithm is used to identify and count the CTOs. Thereafter, other algorithms are presented that are used to identify wind farm- and port visits and transits. These algorithms, and the information they should provide, are discussed in detail in this chapter.

6.1 Identify Crew Transfer Operations

The CTO algorithm is the fundamental algorithm of this project. The aim of this algorithm is to get a list of all executed CTOs. This list includes the MMSI numbers, date and time of the CTOs, duration of the CTOs, turbine identifications and sea state conditions during the CTOs. This information is needed to derive the CTO demand per turbine/ wind farm and to get information about how many CTOs can be executed with a CTV.

6.1.1 Crew Transfer Operation algorithm

In order to extract the required information from the data, the following algorithm is used to identify CTOs from the AIS, sea state and wind farm data. This algorithm is developed based on the knowledge obtained in the previous chapters in a continuous/ feedback-loop process. The algorithm steps are designed by thoroughly analysing the CTO process, inventorying the required output and examining the available data. The output of the algorithm is compared with a validation dataset to improve the algorithm and to find the best settings (see section 6.2 for information about the validation dataset). There are no alternative algorithms to present since it is incrementally developed and adjusted whenever the results were not satisfying. Other data mining algorithms presented in this chapter are developed in a similar manner.

1. Add a wind turbine ID label to an AIS report if:
    a. The SOG <= 1.0 kts; and
    b. The CTV is located within 65 m from a wind turbine, i.e. is in the wind turbine area.
2. Add missing wind turbine ID labels. The highlighted cell in row 7 in Table 10 should get the same 'wt_id' label as row 6 and 8, since in reality the transfer continues. Missing ID labels are added up to 9 consecutive missing values in a row.

3. Calculate the transfer time over continues wind turbine ID labels. In Table 10, this is the time in the red cell of row 9 minus the time in the green cell of row 2.

4. Count as a CTO if the transfer time >= 1 minute.

Table 10: Data sample – add missing wind turbine ID labels count and time crew transfers. Used data from MSG AIS Data Store, table is own composition.

	Date and UTC Time	MMSI	Lat	Lon	SOG	TotalWaves Height (m)	wt_id	transfer_ time
1	10/10/2016 14:54:27	205646000	51.53282	2.924185	3.8	0.85166666		
2	10/10/2016 14:55:29	205646000	51.53303	2.924187	0.7	0.85138888	TH47	0 days 00:07:40
3	10/10/2016 14:56:34	205646000	51.53307	2.92415	0.1	0.85111111	TH47	
4	10/10/2016 14:57:35	205646000	51.53306	2.924148	0.3	0.85083333	TH47	
5	10/10/2016 15:00:06	205646000	51.53301	2.924193	0.0	0.85	TH47	
6	10/10/2016 15:01:09	205646000	51.53303	2.924225	0.4	0.84972222	TH47	
7	10/10/2016 15:01:58	205646000	51.53285	2.924238	1.5	0.84972222		
8	10/10/2016 15:02:08	205646000	51.53278	2.924242	0.9	0.84944444	TH47	
9	10/10/2016 15:03:09	205646000	51.5325	2.924187	1.2	0.84916666		
10	10/10/2016 14:54:27	205646000	51.53282	2.924185	3.8	0.85166666		

Table 10 contains a data sample that is generated to count and time turbine transfers. The first 5 columns are from the AIS dataset. The CTO algorithm checks for each row in the dataset if the SOG is smaller or equal to 1.0 kts. If this is the case, the program calculates the distance between the CTV and all the wind turbines in the wind farm. When the computer finds a distance between the CTV and a wind turbine that is smaller than or equal to 65 m, the computer returns the turbine ID in the 'wt_id' column. After this step, the missing turbine ID labels are added.

The time in the column 'transfer_time' is the difference between the green and red cells in respectively row 2 and 9. The green cell is the first known time for which the CTV has a speed below 1.0 kts and is within 65 m from the turbine. The red cell is the first known time for which at least one of these conditions is not met anymore. Since the frequency of AIS transmission during low speeds (which is the case during crew transfers) could increase to once per 3.5 minutes, the red cell stopping criteria is preferred above using the latest row with a value in the 'wt_id' column. Especially since the transmission frequency rises again when the CTV increases its speed. As will be explained in section 6.1.2.4, an operation is counted as a crew transfer if the transfer time is equal to or longer than 1 minute.

As is explained in section 5.2.2.2, MSG cleaned the data from almost all position jumps, and the few position jumps that are still present in the data are dealt with by adding missing turbine ID labels. However, when a positon jump occurs at the first row of a CTO it could still effect the results. The AIS report in row 2 of Table 11 is a positon jump. In this very rare occasion, the location of the fault AIS report is within the turbine area of AM54, while the CTO is executed at turbine AM18 as is clear from the consecutive AIS reports. The CTO at AM18 is in this case counted by the algorithm as a CTO at AM54. To avoid this, the first turbine ID label of a CTO is made the same as the second turbine ID label. This is only done when the second turbine ID label is the same as the third turbine ID label to avoid incorrect corrections.

Table 11: Data sample – position jump results in a transfer at turbine AM54 instead of AM18. Used data from MSG AIS Data Store, table is own composition.

	Date and UTC Time	MMSI	Lat	Lon	SOG	wt_id	transfer_time
1	5/11/2016 7:46:20	219019775	54.53331	7.716652	1.9		
2	5/11/2016 7:46:30	219019775	54.51667	7.716563	0.6	AM54	0 days 00:07:29
3	5/11/2016 7:46:49	219019775	54.53332	7.716572	0.1	AM18	
4	5/11/2016 7:47:20	219019775	54.53339	7.716542	0.3	AM18	
5	5/11/2016 7:47:49	219019775	54.53338	7.716532	0.2	AM18	
6	5/11/2016 7:48:10	219019775	54.53337	7.716528	0.3	AM18	

6.1.2 Reasoning behind the constraints and settings

Aforementioned, the algorithm is developed based on the knowledge obtained in the previous chapters in a continuous/ feedback-loop process. In practice, this means that the algorithm constraints and settings are initially set based on the obtained knowledge from the CTO process, visual data analysis and expert input. These initial settings are then optimised by comparing the algorithm results with the validation datasets (see section 6.2).

6.1.2.1 Speed over ground

A CTV should not move forwards or backwards when technicians are stepping over from the vessel to the turbine or vice versa. During a transfer, however, a CTV's SOG is not always 0.0 kts since the vessel may move due to wave motions, the stern may sway a little while the bow is pushed to the turbine and the speed may be higher due to minor inaccuracies of the signal. For these reasons, the maximum SOG during transfers is set to 1.0 kts based on analysis of the data, the expertise of MSG and validation of the results.

6.1.2.2 Distance between CTV and turbine

The maximum distance for transfers between turbine and CTV is set to 65 m. This parameter is set by validating the results of a wide range of distance settings. In the theoretical case that the turbine GPS coordinates are exactly known, the maximum distance could be set around 50 m based on the reasoning showed in Figure 25.

It is assumed that the total construction diameter is always below 20 m. Sif Group, a leading offshore foundations manufacture, can produce monopiles with diameters up to 11 m (Sif Group, 2017), which is far under 20 m. The monopiles of Amrumbank, Lincs, Lynn and Inner Dowsing are produced by Sif Group, and have a maximum diameter of 6 m. Less common jacket foundations however, tend to have larger construction diameters. The jackets used in Thornton are for example 18 by 18 m (C-Power, 2017). So, the assumed 20 m is for most wind farms on the safe side.

The antenna of the AIS transmitter is normally placed on top of the bride, next to other navigation and communication equipment. However, in theory it could be placed anywhere between the bow and the stern of the CTV. So, in an extreme case the AIS location corresponds to the stern of a CTV. This means that the distance between the turbine and the transmitted location during transfers could be the full length of the CTV.

According to MSG, the inaccuracy of the GPS signal is at most 5 m. When adding these numbers, the distance should be at least 50 m. In practice, however the turbine location may not be exactly known, and therefore the distance should be increased to ensure that the locations of AIS reports transmitted during transfers are within the given radius from the turbine.

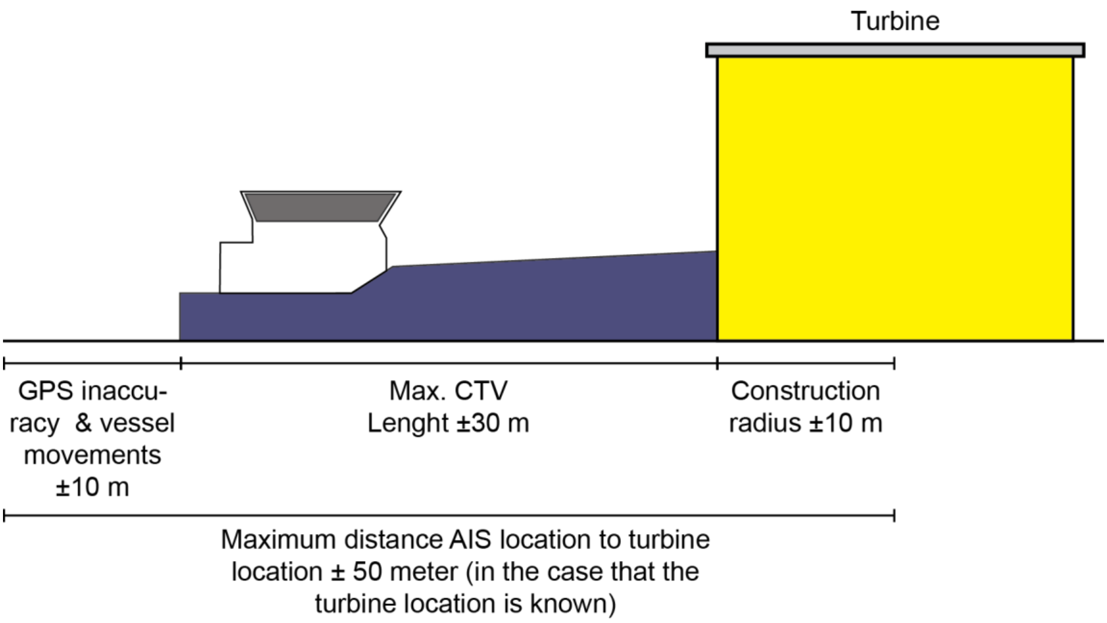

Figure 25: Maximum distance between AIS location and turbine for transfers. Source: own composition.

Increasing the radius may cause faults in the algorithm's output. Figure 26 illustrates a CTV that drifts through the turbine area of TH16. This movement is erroneously counted as a transfer by the algorithm. When decreasing the radius of the turbine area, the vessel will not enter the turbine area in this specific case and will therefore not be counted as a transfer. However, when making the turbine area smaller it may happen that true transfers will not be executed within the set radius from the turbine and therefore are missed by the algorithm. This plays especially a role when the estimated turbine coordinates are less accurate. As can be seen in Figure 27, the turbine area required to count all true transfers becomes significantly larger when the estimated turbine location is 30 m off from the actual turbine location. Accuracy of the turbine locations is therefore of the utmost importance. For Amrumbank, the actual turbine locations are known for 6 turbines. The used locations based on the DBSCAN are for these 6 turbines between 20 and 24 m off. This deviation is assumed to be fit for purpose for this project.

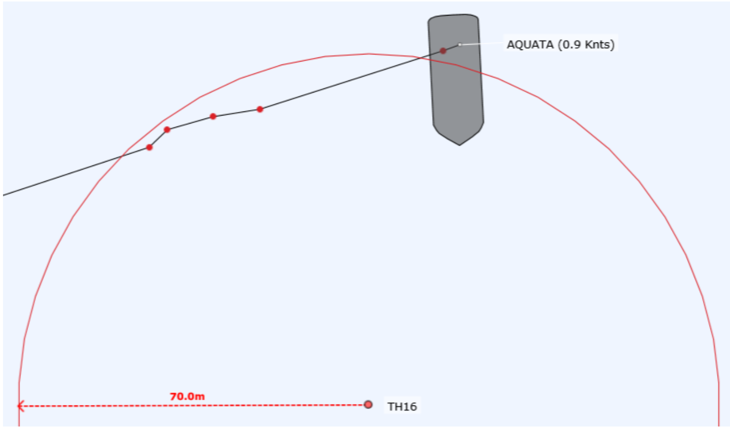

Figure 26: Example of CTV drifting through a wind turbine area. Figure composed in MSG Plotter.

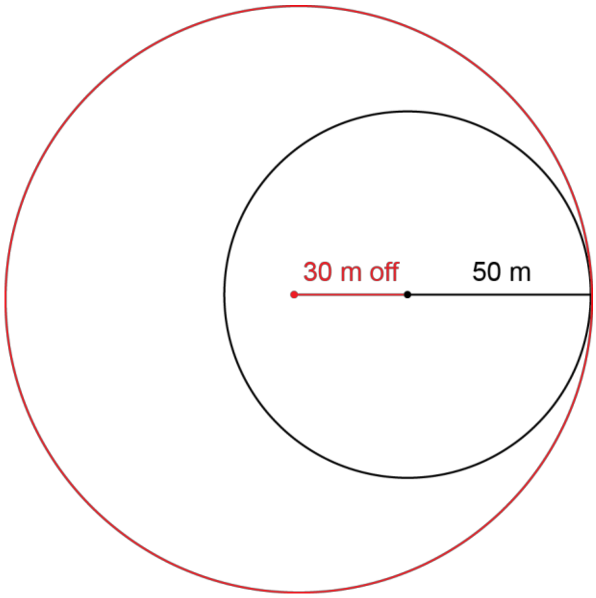

Figure 27: Turbine areas and radius for the case that the location is known (black) and for the case that the estimated location is 30 meters off (red). Source: own composition.

The distance between the AIS reports' GPS coordinates and the turbines is calculated with the equirectangular approximation that is based on Pythagoras and adjusted for spherical shapes. The distance could be calculated more precisely with the complex haversine formula. However, this method consumes much more computing power. The accuracy of the outcome of the equirectangular approximation is sufficient for this project, since the distances of interest are relatively small (up to 100 m). The formula of the equirectangular approximation is as follows:

$$a = (lon_{WT} - lon_{AIS}) * \cos(\,^{1}/_{2}\ (lat_{WT} + lat_{AIS}))$$

$$b = lat_{WT} - lat_{AIS}$$

$$Distance = r * \sqrt{a^2 + b^2}$$

With:

lon	=	*Longitude*
lat	=	*latitude*
WT	=	*wind turbine*
AIS	=	*Automatic Identification System*
r	=	*radius of the earth (6371000 meter)*

6.1.2.3 Missing turbine ID labels

As shown in Table 10, it may happen that an AIS report is not labelled with a turbine ID label, although the CTV was executing a CTO. There are three primary reasons for this: the SOG was temporarily above 1.0 kts or the CTV was temporarily not within the turbine area due to a position jump or because the transfer is being executed on/ just within the border of the turbine area. When there are one or more missing turbine ID labels in consecutive rows, the algorithm counts multiple transfers instead of one. Therefore, it is necessary to add the missing turbine ID labels. Missing turbine ID labels are added up to a maximum of 9 consecutive AIS reports. This number is set by comparing the results of different numbers with the validation dataset.

6.1.2.4 Minimum transfer time

Aforementioned in section 3.4.1: technicians could step over from the CTV to the turbine within 30 to 60 seconds. Some additional time is needed for approaching, docking and leaving the turbine. Therefore, it is assumed that a transfer cannot be executed in less than 1 minute. When relaxing this constraint, the number of erroneously counted transfers increases, which is tested based on the validation dataset.

6.2 Validation of the Crew Transfer Operation Algorithm

The output of the CTO algorithm is compared with a validation dataset. As mentioned, this comparison is used in a continuous/ feedback-loop process to develop the algorithm. The validation dataset is created with MSG Plotter. In this tool, it is possible to upload the locations of the wind turbines and to animate the CTV movements based on AIS data. This enables identifying and timing CTOs by hand, and thus creating a dataset in the same format as the output dataset of the CTO algorithm. For the three selected wind farms, the executed CTOs for at least one CTV over a period of one week is counted by hand. This results in several datasets that are used to validate the settings of the algorithm.

6.2.1 Testing algorithm settings

Four parameters can be set in the CTO algorithm: the number of consecutive rows for which missing turbine ID labels are added; the maximum speed during transfers; the minimum distance between the CTV and the turbine for transfers; and the minimum duration of a transfer. By varying these parameters, 21 different combinations are tested for one CTV that was operational in Amrumbank. The results of these settings are depicted in Table 12 on page 55, and compared based on the following categories.

- **Transfers Counted** is the total transfer output of the algorithm.
- **Correctly Counted** are transfers counted correctly by the algorithm.
- **Not Counted** are transfers that are missed by the algorithm.
- **Counted Double** means that one transfer is counted as two transfers (one as 'correctly counted' and one as 'counted double').
- **Erroneously counted** refers to a counted transfer that was not executed.
- **F1-score** is the average of the precision and recall of the outcome.

The following procedure is used to vary the settings and to identify good working algorithms. The initial settings are chosen in such a manner that the algorithm would count too much transfers. These initial settings are then optimised in accordance with their expected effect on the results in order to find the best combination of settings.

1. First, the number of consecutive rows for which missing turbine ID labels are added is increased from 0 up to 9 rows. This is done to eliminate the number of double counted transfers, however, when adding too much rows two transfers executed shortly after each other will be counted as one transfer. As can be seen in Table 12, the number of double counted transfers remained unchanged for adding up to 3, 5, 7 and 9 consecutive rows with missing turbine ID labels. The number of total yearly counted transfers, however, keeps falling when increasing the number of added rows. At this point it is decided to continue with algorithm 4 (adding up to 5 rows) to avoid that two true transfer will be counted as one.
2. The maximum distance between the CTV and the turbine is decreased from 80 m to 50 m (which is the theoretical lower limit). This is done to eliminate the number of erroneously counted transfers, as is explained in section 6.1.2.2. When making the distance too small, however, transits may be executed outside the turbine area. The number of total yearly transfers increases between algorithm 8 and 9 (70 m and 65 m), which may indicate that the radius in algorithm 9 is set too low for the following reason: transfers executed on the edge of the turbine area may be split into two counted transfers because a part of the operation may be executed outside the set turbine area. Therefore, it is decided to continue with a maximum turbine distance of 70 m.

3. The influence of the maximum SOG and the minimum transfer time is tested in algorithms 15 and 16. Based on these results, it is concluded that the initial settings of 1.0 kts and 1 minute are likely to give the best results.
4. At last, the number of rows for which missing turbine ID labels are added is again increased to test whether the maximum distance between CTV and turbine would have an effect on the algorithm output. The maximum tested number of rows is 11.

The tested algorithm settings and their results are shown in Table 12. The most promising algorithms (printed bold and italic) are verified for the other validation datasets as well, for which similar tables are presented in Appendix G. The overall best performing algorithm is number 20 (highlighted in green) as is explained in the next section.

Table 12: CTO algorithm validation results for Amrumbank, MMSI 219019775, period 5/7/16 – 5/13/16. Source: own composition.

Algorithm	Transfers counted	Correctly counted	Not counted	Counted double	Erroneously counted	Turbine locations	Max SOG [kts]	Max turbine distance [m]	Min transfer time [min]	Adding missing turbine ID labels [up to x rows]	F1-score
Validation	**103**	-	-	-	-	-	-	-	-	-	-
1	109	103	0	4	2	DBSCAN	1	80	1	0	97.2%
2	106	103	0	1	2	DBSCAN	1	80	1	1	98.6%
3	105	103	0	0	2	DBSCAN	1	80	1	3	99.0%
4	104	103	0	0	1	DBSCAN	1	80	1	5	99.5%
5	104	103	0	0	1	DBSCAN	1	80	1	7	99.5%
6	104	103	0	0	1	DBSCAN	1	80	1	9	99.5%
7	***104***	***103***	***0***	***0***	***1***	***DBSCAN***	***1***	***75***	***1***	***5***	***99.5%***
8	***104***	***103***	***0***	***0***	***1***	***DBSCAN***	***1***	***70***	***1***	***5***	***99.5%***
9	***104***	***103***	***0***	***0***	***1***	***DBSCAN***	***1***	***65***	***1***	***5***	***99.5%***
10	***104***	***103***	***0***	***0***	***1***	***DBSCAN***	***1***	***60***	***1***	***5***	***99.5%***
11	105	103	0	1	1	DBSCAN	1	55	1	5	99.0%
12	105	103	0	1	1	DBSCAN	1	50	1	5	99.0%
13	106	103	0	0	3	DBSCAN	1	70	0	5	98.6%
14	92	92	11	0	0	DBSCAN	1	70	2	5	94.4%
15	104	102	1	1	1	DBSCAN	0.5	70	1	5	98.6%
16	105	103	0	0	2	DBSCAN	1.5	70	1	5	99.0%
17	***104***	***103***	***0***	***0***	***1***	***DBSCAN***	***1***	***70***	***1***	***7***	***99.5%***
18	***104***	***103***	***0***	***0***	***1***	***DBSCAN***	***1***	***70***	***1***	***9***	***99.5%***
19	***103***	***102***	***1***	***0***	***1***	***DBSCAN***	***1***	***70***	***1***	***11***	***99.0%***
20	***104***	***103***	***0***	***0***	***1***	***DBSCAN***	***1***	***65***	***1***	***9***	***99.5%***
21	***103***	***102***	***1***	***0***	***1***	***DBSCAN***	***1***	***65***	***1***	***11***	***99.0%***

6.2.2 Selecting the best performing settings

To select the best performing algorithm settings, two factors are used and equally weighted. The first factor is the F1-score (F1), which is a widely-used method to measure the accuracy of e.g. machine learning projects (Powers, 2011). Although other methods are considered to give better results, the F1 is chosen for this case for the following reason: the number of True Negatives (the opposite of True Positives) needed to measure the accuracy better are not at hand for this project.

The F1 is the average of the precision (percentage of correctly counted transfers of all counted transfers) and recall (percentage of correctly counted transfers of all transfers) and can be calculated with the following formula:

$$F1\ score = 2 * \frac{precision * recall}{precision + recall} = \frac{2 * TP}{2 * TP + FP + FN}$$

With:

$TP \quad = \quad True\ Positives\ (counted\ correctly)$

$FP \quad = \quad False\ Positives\ (counted\ double + erroneously\ counted)$

$FN \quad = \quad False\ Negatives\ (not\ counted)$

Secondly, the percentage of correctly counted transfers (C.C.) should be as high as possible. The C.C. is the recall of the output, and can be calculated by dividing the number of correctly counted transfer by all executed transfers. This factor is added to the selection because the F1 score gives equally good results for algorithm 19, 20 and 21 (see Table 13). By averaging the recall and the F1, the recall weighs more heavily than the precision. This is done deliberately because correctly counting true transfers is considered to be more important than having a few not counted, counted double or erroneously counted transfers.

Table 13: Percentage of correctly counted transfers & F1-score for the most promising algorithm settings (18, 19, 20 and 21). Source: own composition.

	Lina		MV Carrier		Windcat 9		Aquata			
	F1	**C.C.**	**F1**	**C.C.**	**F1**	**C.C.**	**F1**	**C.C.**	**Average F1**	**Average C.C.**
18	99.5%	100.0%	100.0%	100.0%	98.9%	100.0%	99.1%	100.0%	99.4%	100.0%
19	99.0%	99.0%	100.0%	100.0%	100.0%	100.0%	99.1%	100.0%	99.5%	99.8%
20	99.5%	100.0%	100.0%	100.0%	99.3%	100.0%	99.1%	100.0%	99.5%	100.0%
21	99.0%	99.0%	100.0%	100.0%	100.0%	100.0%	99.1%	100.0%	99.5%	99.8%

Table 13 shows the percentage of F1 and C.C. for the most promising algorithm settings for all CTVs for which a validation dataset is available. The last two columns include the average F1 and C.C. scores of the validation results. As can be seen, algorithm 20 performs slightly better than the other algorithms, and is therefore selected. The selected settings are:

- **Max. SOG during transfers:** 1.0 kts
- **Max. distance between CTV and turbine:** 65 m
- **Min. transfer time:** 1 minute
- **Adding missing turbine ID labels:** up to 9 rows

In some cases, the F1 and C.C. are the same for different algorithm settings, while the number of total counted transfers per year vary slightly. To eliminate this, a more extensive validation dataset is needed. However, creating this dataset will consume a lot of time that is not available. Moreover, MSG and Damen are convinced that the current accuracy of the algorithm is fit for purpose.

6.3 Other Data Mining Algorithms

Apart from the actual crew transfers, statistics of other elements of the CTO's logistic process are necessary to model CTV demand. This section presents the other data mining algorithms that are used to derive the required information from these elements.

6.3.1 Wind farm visits

This algorithm is used to get information about the wind farm visits of all CTVs. The aim of this is to get information about the required number of CTV working days per wind farm, sea state conditions during wind farm visits, duration of the visits, visits per CTV and visits per wind farm. This information is needed for both the demand of the wind farm and the supply of the CTVs.

1. Define a polygon shape of the wind farm area based on GPS coordinates of the corner turbines (process is described in section 5.4.1) and give each wind farm a unique wind farm ID.
2. If the GPS coordinates of an AIS report are within the wind farm area, add the wind farm ID label to the AIS data.
3. Similar to adding the missing turbine ID labels, missing wind farm ID labels are added up to 5 consecutive rows.
4. Calculate wind farm time over continues wind farm ID labels, similar to the method used to calculate transfer time.
5. Determine number of CTV working days. The wind farm visits in rows 4, 5 and 6 in Table 14 all have the same date. This is due to the fact that the CTV crossed the border of the wind farm multiple times

on that day. These three wind farms visits are counted as one CTV working day, since the vessel was clearly working in/ for the wind farm on that day.

This algorithm results in a table similar to Table 14. This table can be used to get e.g. statistical information about the yearly number of CTV days per wind farm.

Table 14: Data sample - counting wind farm visits. Used data from MSG AIS Data Store, table is own composition.

	Date and UTC Time	MMSI	Lat, Lon, SOG, Wind and sea state data	wf_id	wf_time
1	1/1/16 8:10:11	253415000	---	TH	0 days 03:18:01
2	1/5/16 12:24:38	253415000	---	TH	0 days 00:15:32
3	1/6/16 7:23:06	253415000	---	TH	0 days 09:30:27
4	1/18/16 7:41:08	253415000	---	TH	0 days 03:07:31
5	1/18/16 11:01:39	253415000	---	TH	0 days 02:08:16
6	1/18/16 15:11:10	253415000	---	TH	0 days 01:30:13
7	1/19/16 7:30:26	253415000	---	TH	0 days 00:33:35

6.3.2 Port visits

This algorithm has a similar working as the ‘wind farm visits’ algorithm. The required information is when CTVs enter and leave the port. This is among others needed to obtain information about the transits between port and wind farm.

1. Define a polygon shape of the port area based on GPS coordinates and give the port an ID label.
2. The port ID label is added to an AIS report if the GPS coordinates are within the polygon that describes the port area.
3. Similar to adding the missing turbine ID labels, missing port ID labels are added up to 5 consecutive rows.
4. Calculate port time over continuous port ID labels, similar to the method used to calculate transfer time.

6.3.3 Transits

Transits from onshore/ offshore maintenance hubs to wind farms and vice versa consumes a lot of precious working time. It is important to gain insights in the duration of transits, because this has a direct influence on the number of CTVs needed to provide the wind farm in its CTO demand. The transits logarithm should provide the information required to calculate the transit time. This can be done based on an analysis of the transit time, distance, speed and sea state conditions of all executed transits. The following algorithm is developed to translate the data into the required information.

- The AIS reports corresponding to the transits are labelled.
    a. The data between AIS reports labelled with a port ID and a wind farm ID are labelled as ‘port transit’
    b. The data between AIS reports labelled with a wind farm ID and a port ID are labelled as ‘wind farm transit’
    c. The data between AIS reports that are both labelled with a wind farm/ port ID label are not labelled as a transit, because in these cases the CTV did not sailed from the port to the wind farm or vice versa.
- The transit time is calculated over continuous transit labels, similar to the method used to calculate transfer time.
- The transit distance is calculated over continuous transit labels:
    a. Calculate the distance between the GPS coordinates of two consecutive AIS reports with the equirectangular approximation.
    b. Sum the distances between consecutive AIS reports over continuous transit labels to calculate the total sailed distance (this is an approximation).
- Calculate the mean SOG during transfers by dividing transit distance by transit time. The distribution of the SOG during the transits is not taken into account, since only the mean SOG is assumed to be relevant for the CTV Demand Model.
- Remove outliers:
    a. Transits with a mean SOG >= max. vessel speed are removed. The mean SOG could be extremely high due to position jumps. According to the data, the CTV sailed in these cases hundreds of nm within a few seconds resulting in an extremely high SOG.
    b. Transits with a mean SOG <= 7.0 kts. are removed from the data because these transits are considered to be abnormal.
    c. Transits with a transit distance that is 20% larger or smaller than the distance from the port to the wind farm are removed for the same reasons as the transits with a mean SOG <= 7.0 kts.

6.4 Limitations of the Data Mining Algorithms

The used algorithms have some limitations that are discussed in this section. Furthermore, an improvement for the algorithm are suggested.

First of all, in some cases it is unambiguous if a CTV movement was a crew transfer or not. An example of such a movement is illustrated in Figure 28. The two green AIS reports are located close to the turbine, the time between the AIS reports was just over 1 minute, and the SOG was below 1.0 kts. This means that all set conditions for a CTO are met, so the algorithm counts this movement as a transfer. Most transfers, however, consist of more AIS reports and/ or AIS reports with (nearly) the same location. For this reason, it is not certain if the movement in Figure 28 illustrates a crew transfer. In this case, the CTV may have instead executed e.g. a visual inspection.

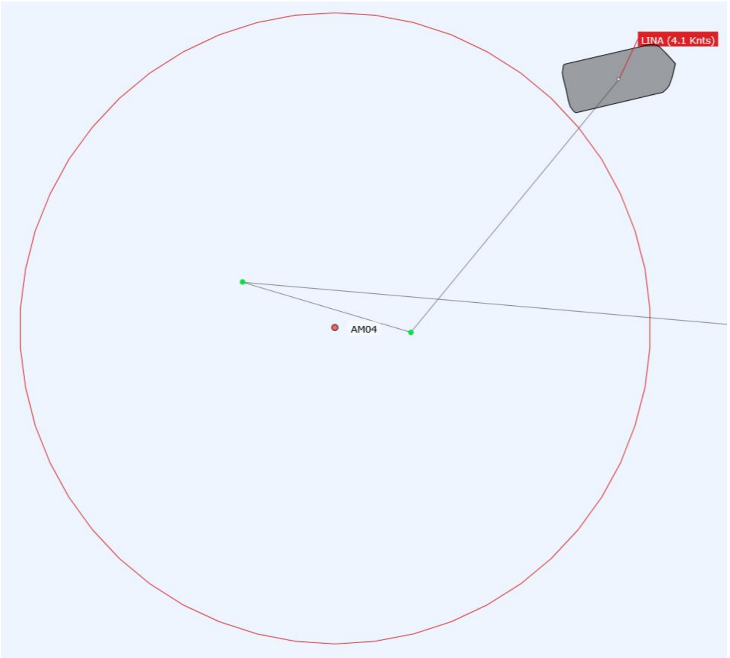

Figure 28: Example of unambiguous movement. It is not clear if this should be counted as a transfer or not. Figure composed in MSG Plotter.

Secondly, during the creation of a validation dataset for Lynn Inner Dowsing, manoeuvres similar to the one illustrated in Figure 29 are identified. The two opposite clusters of AIS reports closest to the turbine are CTOs. In the animation of MSG Plotter can be seen that the CTV sailed backwards after the CTOs to the location where the vessel is shown in the figure. From there, the vessel started drifting very slowly in a circle around the turbine, as if it was moored to the turbine. After a few hours, the vessel sailed back to one of the AIS clusters closest to the turbine to pick-up the technicians.

This manoeuvre influences the algorithm results in two manners: first, the crew transfer time is extremely long because the transfer and spinning around the turbine is counted as one transfer due to adding missing turbine ID labels; or the transfer and spinning around the turbine are counted as two transfers, while the latter is not a transfer.

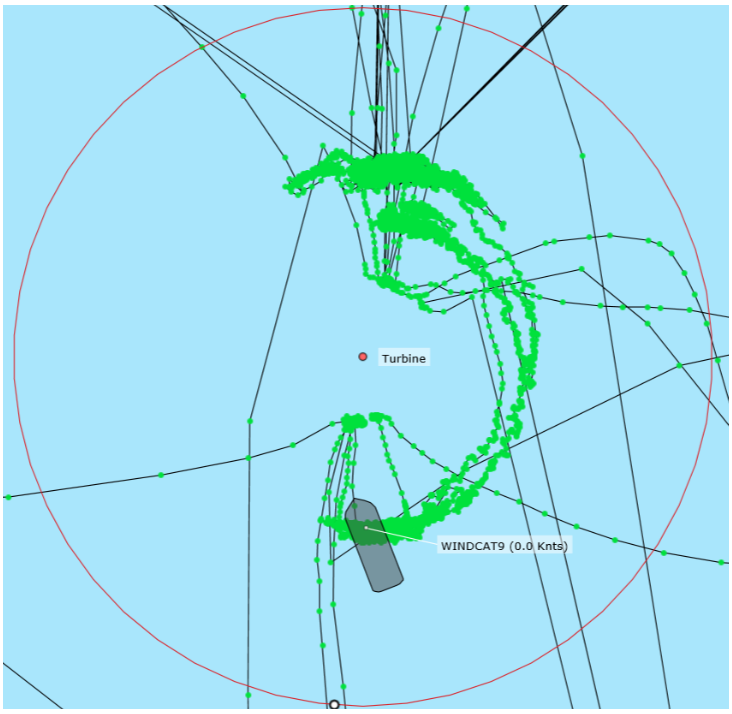

Figure 29: Transit and idle in the wind turbine area. It seems that this CTV is moored to the turbine when idle. Figure composed in MSG Plotter.

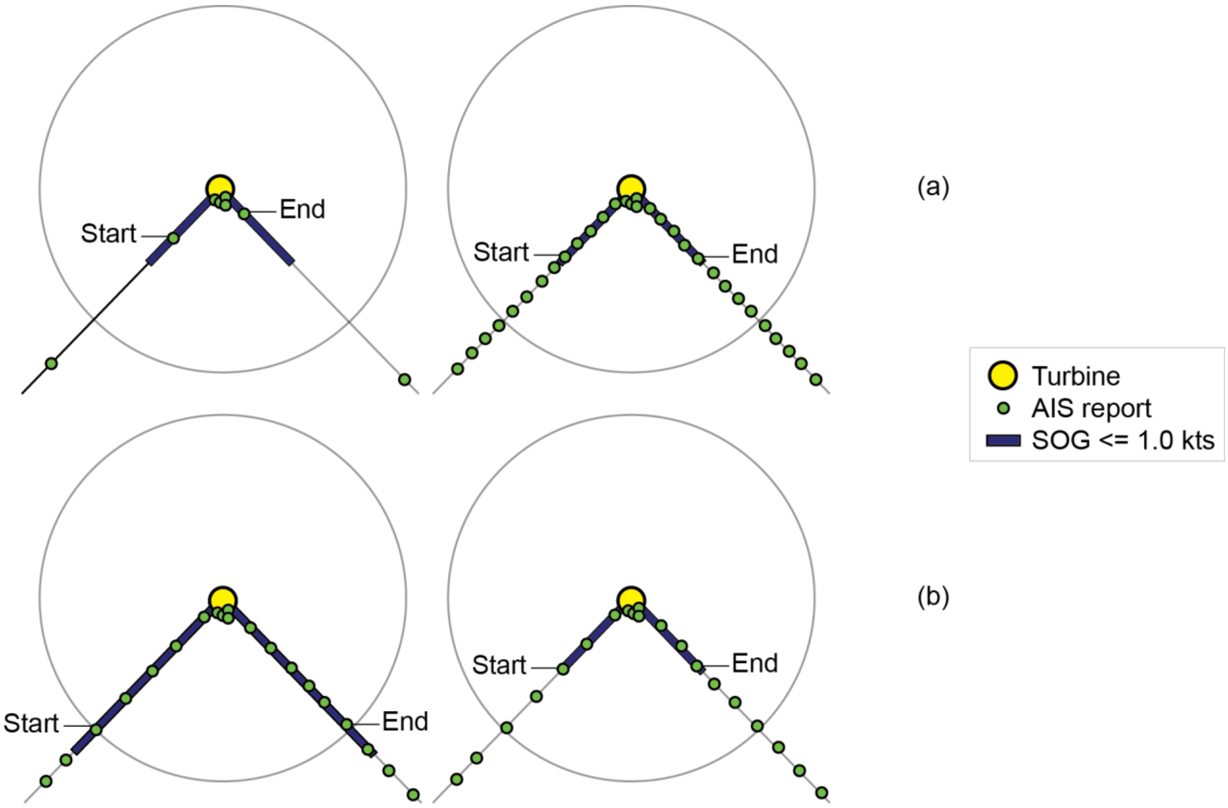

Figure 30: (a) density of AIS reports and (b) different approaches influences the measured CTO time. Source: own composition.

The third limitation is the impossibility to exactly time the duration of transfers due to the variation of the time deltas between AIS reports and the variation in how CTVs approaches the turbine. In both cases, this is caused by the method to identify a crew transfer: the start is the first AIS report for which all conditions are met, and the end is the first AIS report for which one of the conditions is not met anymore. Figure 30 (a) and (b) illustrate respectively how the density of AIS reports and turbine approach influences the starting and end point of the counted CTOs.

Fourth, aforementioned in section 6.1.2.2, a CTV could drift through a wind farm area when idle. These movements may be counted as a transfer by the algorithms. More precise GPS coordinates of the wind turbines could eliminate this problem. The circle around the turbine could then be set smaller, which minimises the probability that a CTV drifts trough the wind turbine area.

The last point is a point of improvement instead of an algorithm limitation: the missing turbine, port and wind farm ID labels are now added up to x rows. It may be better to add missing ID labels up to y minutes, since the time deltas between rows could differ significantly. Adding ID labels based on a maximum time interval would therefore be a more consistent method.

This chapter elaborated on the data mining algorithms that are used to translate among others AIS data into the required information about the CTO process. This information is presented in the next chapter.

7 Crew Transfer Operation Statistics

The data mining processes presented in the previous chapter resulted in information about the executed CTOs in the Amrumbank, Lynn Inner Dowsing and Thornton in 2016. This information is statistically analysed and visualised, of which the results are presented in this chapter. These results can be used to gain insights into the CTO process and it is used as input for the CTV Demand Model.

7.1 Crew Transfers

The information obtained from the CTO algorithm is used to gain insights into the crew transfers from two perspectives; the executed crew transfers per turbine provide insights into the CTO demand; and the crew transfers executed per vessel is used to analyse the demand side. Both sides of the CTOs are discussed in this section.

7.1.1 Crew Transfer Operation demand

Figure 31 shows the histograms and gamma distributions of the counted CTOs per wind turbine for all three analysed wind farms for the year 2016. Furthermore, the combined gamma distribution is plotted. This distribution is used in the CTV Demand Model to simulate the CTO demand per wind turbine. For each wind farm, a separate histogram and gamma distribution is included in Appendix H.

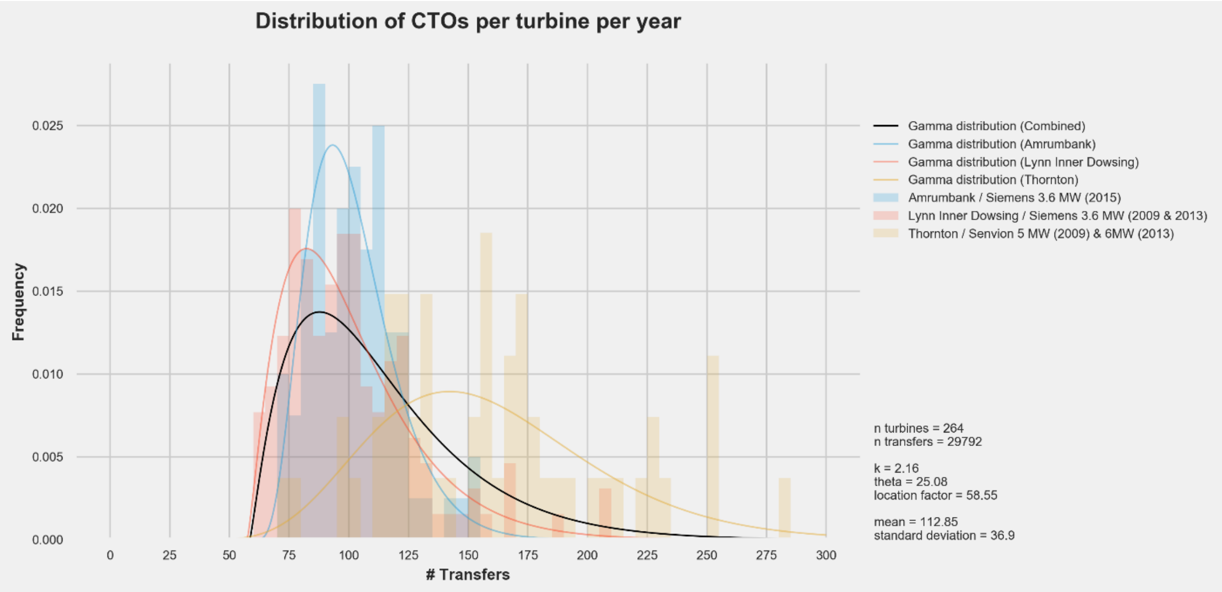

Figure 31: Distribution of transfers per turbine in 2016. Source: own composition.

As can be seen in Figure 31, the demand for CTOs per wind turbine was higher for Thornton than for Amrumbank and Lynn Inner Dowsing. The mean number of transfers per turbine in 2016 was for these wind farms respectively 159.2, 101.5 and 100.6. This substantial difference may be explained by the variation in turbine make. As indicated in the legend, Amrumbank and Lynn Inner Dowsing both have 3.6 MW Siemens turbines, hence their distributions are quite similar (For the Siemens turbines of Amrumbank and Lynn Inner Dowsing a separate histogram and combined gamma distribution is included in Appendix H).

Thornton on the other hand, has 6 relatively old 5 MW Senvion turbines and the other 48 are more modern 6 MW turbines from the same manufacturer. $^2/_3$ of the old 5 MW turbines required more than 200 CTOs in 2016. This is of course an extremely high CTO demand that influences the overall demand of Thornton. However, the mean CTO demand of the newer 6 MW turbines was 151.5 in 2016. This demand is still much higher than the CTO demand of Amrumbank and Lynn Inner Dowsing.

7.1.1.1 Crew Transfer Operation demand: Automatic Identification System vs. literature

Aforementioned, the average CTOs per turbine for Amrumbank, Lynn Inner Dowsing and Thornton are respectively 159.2, 101.5 and 100.6 for the year 2016. These figures are much higher than the demand of 50 CTOs per turbine per year that is derived from the literature in section 2.3. This significant difference may be explained by the following reasons.

First of all, the figures presented in the literature may simply be too optimistic. The used information from some of the papers is obtained via operators and industry players, who may have presented the best-case scenario.

Secondly, it is assumed in section 2.3 that a turbine visit consists of 1 drop-off and 1 pick-up of technicians, resulting in 2 CTOs per turbine visit. This number may be higher, as e.g. extra CTOs are performed to transfer spare parts or to drop-off/ pick-up technicians during the maintenance tasks.

Furthermore, it is assumed that technicians may stay up to 7 hours on the turbine. With hindsight, this may be too long, meaning that more CTOs should be executed per repair job.

Thirdly, it is not in all the papers clear which maintenance tasks are included in the presented figures. Based on the publication from SPARTA (2017) for example, is assumed that each turbine requires 48-64 CTOs per year for repairs. It is not clearly mentioned in the publication if the planned maintenance is included or not. When this is not included, the total CTO demand per turbine per year is evidently higher.

Fourth, 2016 may have been a terrible year with extremely high failure rates/ a year in which a large maintenance programme is carried out. However, this is not very likely for Amrumbank and Lynn Inner Dowsing (which has the same turbines) as their CTO demand is nearly the same. For Thornton, this may be the case.

7.1.1.2 Seasonality of Crew Transfer Operation demand

As mentioned, the CTO demand distribution is used to model the number of transfers required per turbine per year in the CTV Demand Model. However, the CTO demand is not constant over the year due to the seasonality of the offshore wind industry. The planned maintenance, for example, is normally carried out during the summer months when the sea states are relatively calm. This results in a peak in CTO demand during the summer campaigns. Therefore, the yearly CTO demand is distributed over the months in the CTV Demand Model to incorporate the seasonality.

Table 15 shows the monthly distribution of the total executed CTOs in the analysed wind farms in 2016. As can be seen in the table, the distribution per wind farm differs greatly. This is among others caused by the accessibility of the wind farms, the planning of maintenance activities and the availability of material. The last column shows the average percentage of executed CTOs per month, which is used in the CTV Demand Model to distribute the yearly CTO demand. If the total yearly CTO demand is e.g. 10,000, then the demand in March is 8% of this/ 800 CTOs.

Table 15: Total CTOs executed in the wind farm per month in 2016. Source: own composition.

	Amrumbank		Lynn Inner Dowsing		Thornton		Average
January	308	3.8%	640	4.9%	205	2.4%	3.7%
February	402	5.0%	817	6.2%	215	2.5%	4.6%
March	842	10.4%	1152	8.8%	421	4.9%	8.0%
April	570	7.0%	1140	8.7%	518	6.0%	7.3%
May	1326	16.3%	1139	8.7%	892	10.4%	11.8%
June	1134	14.0%	1399	10.7%	1052	12.2%	12.3%
July	925	11.4%	1618	12.4%	1251	14.6%	12.8%
August	862	10.6%	1321	10.1%	1063	12.4%	11.0%
September	1183	14.6%	1455	11.1%	1378	16.0%	13.9%
October	439	5.4%	742	5.7%	854	9.9%	7.0%
November	75	0.9%	788	6.0%	336	3.9%	3.6%
December	52	0.6%	868	6.6%	410	4.8%	4.0%
Total	8118	100.0%	13079	100.0%	8595	100.0%	100.0%

7.1.2 Crew Transfer Operation supply

The crew transfer supply can be expressed as the average number of transfers executed per hour. Figure 32 illustrates the histograms and gamma distributions of the daily average transfers per hour. The daily average is calculated for each CTV working day by dividing the total executed transfers by the in-field time. As can be seen in the figure, the number of transfers that can be executed per hour differ slightly per wind farm. This difference may be caused by several factors such as the type of maintenance tasks executed, CTVs' technician capacity (all vessels but three have a capacity of 12 technicians) and human factors. The presented distribution of CTOs per hour is used in the CTV Demand Model to simulate the daily executed transfers per CTV.

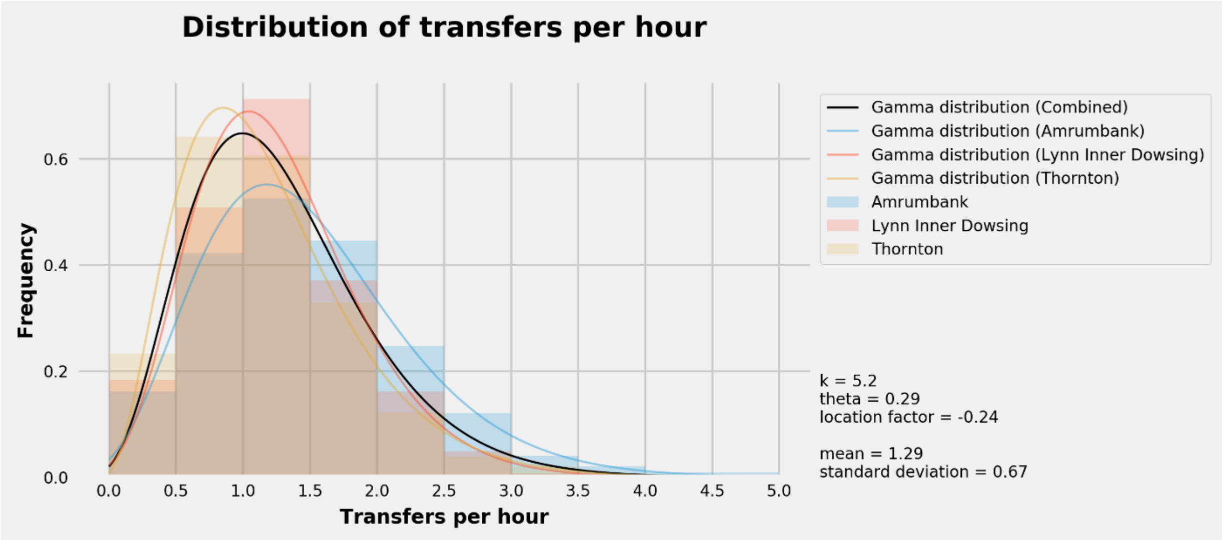

Figure 32: Distribution of transfers per hour (transfers per day divided by in-field working time). Source: own composition.

The crew transfers are executed throughout the whole working day as can be seen in Figure 33. As expected, there is a peak in executed transfers at the beginning and at the end of the working day. In the beginning of the day, the CTVs drop-off all the technicians at different turbines. Depending on the maintenance task, the technicians are picked-up and brought to a next turbine through the course of the day. Evidently, all technicians are picked-up at the end of the day, causing the second peak. The CTV Demand Model works with a constant transfer rate during the day. This does not influence the results, since the CTV demand is simulated on a daily level.

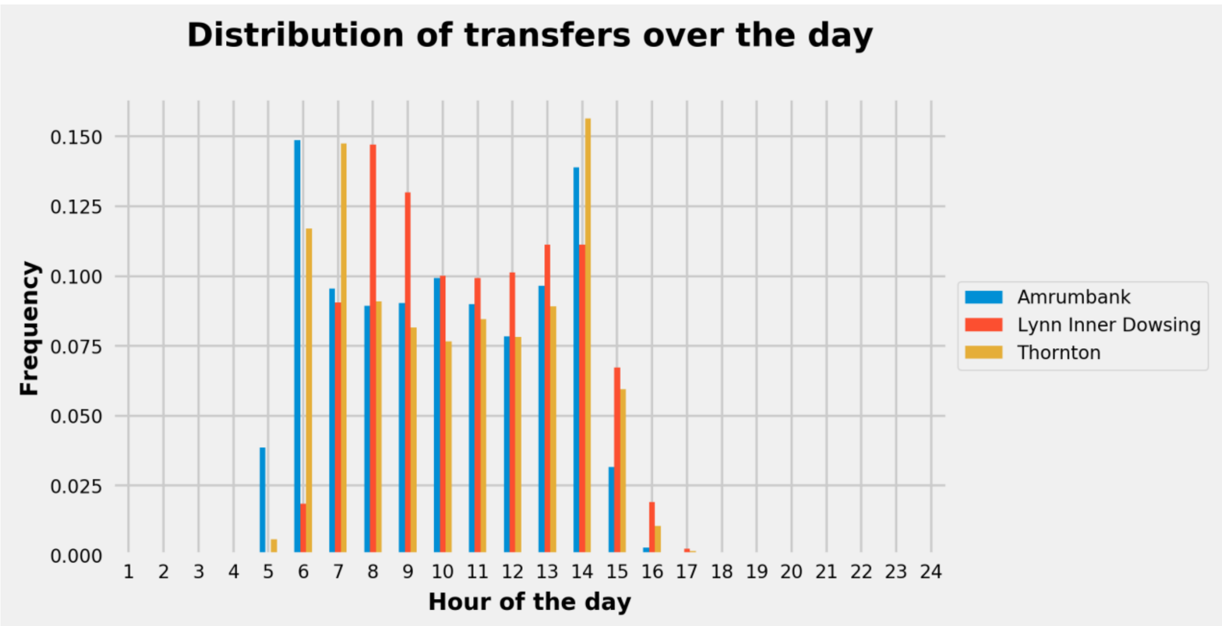

Figure 33: Distribution of transfers over the working days. Source: own composition.

Three of the analysed CTVs have a capacity of 24 technicians instead of the common capacity of 12. These three vessels where all active in Amrumbank. Although in theory possible, the vessels with a higher capacity did not execute more transfers per hour in the Amrumbank case as can be seen in Figure 34. This may be caused by several reasons. First, the number of technicians transferred per CTO may have been higher. This may for example be needed for specific maintenance tasks. Secondly, the capacity may not have been used fully. Damen notices that the vessels with a capacity of 12 technicians is still preferred by many operators, which may indicate that this is currently the optimal capacity. There is no specific transfer supply distribution made for the CTVs with a capacity of 24 technicians, since three vessels are considered to be too little to get reliable statistics.

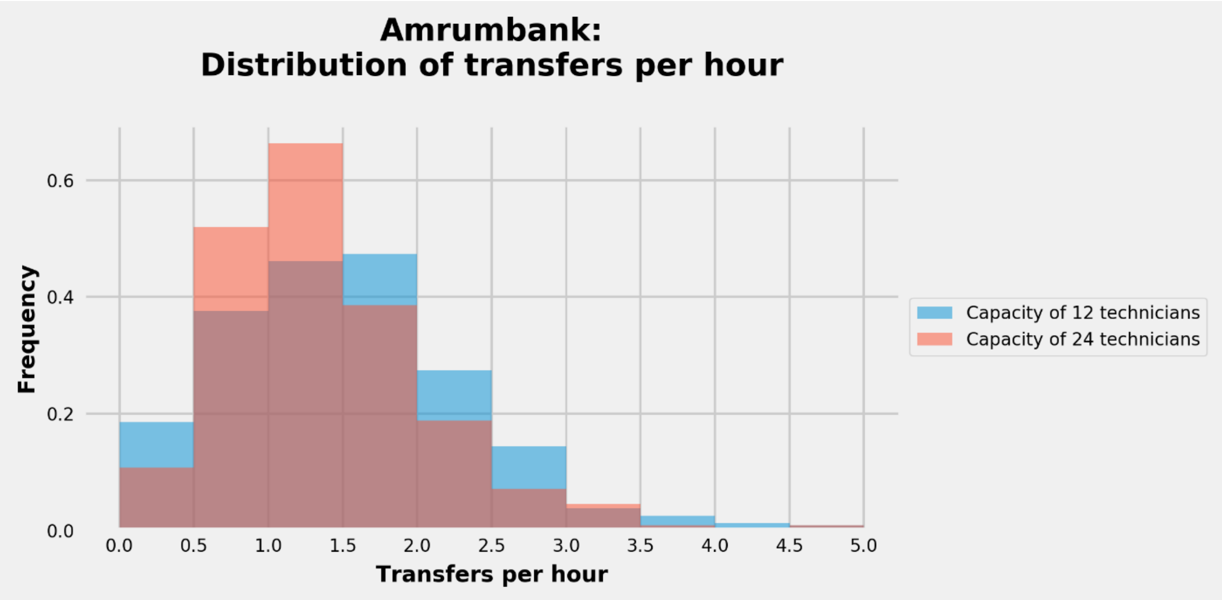

Figure 34: Distribution of transfers per hour. Capacity of 12 technicians versus 24 technicians. Source: own composition.

7.2 Wind Farm Visits

The wind farm visits are used for two purposes. First, the weather window of CTOs is determined; and secondly, the CTV availability is calculated.

7.2.1 Weather window

The seasonality of the offshore wind industry is a direct result of the weather window of CTOs. Figure 35 illustrates the mean Hs during wind farm days. As can be seen, the probability that a CTV visits a wind farm on a day that the mean Hs is higher than 1.5 m is very small. Therefore, all days with a Hs > 1.5 m are considered as non-access days in the CTV Demand Model, which means that no transfers can be executed on those days.

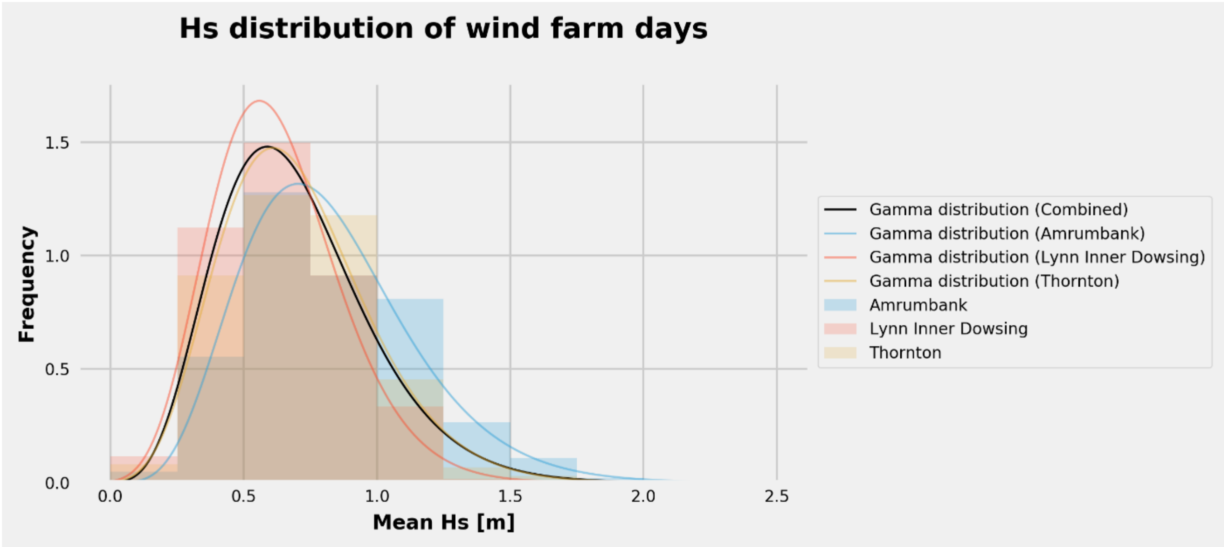

Figure 35: Distribution of the mean Hs (between 6am & 6pm) during wind farm days. Source: own composition.

7.2.2 Crew Transfer Vessel utilisation

The CTV utilisation is calculated via two methods: based on the wind farm visits; and, based on the CTV sailing days. Both methods are elaborated in this section.

7.2.2.1 Utilisation based on wind farm visits

The seasonality of the industry is also reflected in the number of CTV working days per month as can be seen in Figure 36. In this figure, one CTV working day represents one CTV working one day in the wind farm (there is no differentiation made between the length of working days). Evidently, more CTVs are needed to carry out the CTV working days in the summer months relatively to the winter months. This is reflected in Figure 37, which illustrates the mean number of CTVs working in the wind farm. Based on these figures, the mean number of working days per CTV can be calculated with the following formula:

$$Mean\ number\ of\ working\ days\ per\ CTV = \frac{Total\ CTV\ working\ days}{Mean\ number\ of\ CTVs\ working\ in\ the\ wind\ farm}$$

The mean number of working days per CTV, together with the wind farm availability (based on the 1.5 m Hs limit) is used to calculate the CTV utilisation. The utilisation is defined as the percentage of days on which a CTV worked, in relation to the days on which the wind farm was accessible. E.g. if a wind farm is 20 days of the month accessible, and the CTV worked on 10 of these days in the wind farm, then the CTV utilisation is 50%. The utilisation can be calculated with the following formula:

$$CTV\ utilisation = \frac{Wind\ farm\ access\ days\ (\%)}{Mean\ number\ of\ woring\ days\ per\ CTV\ (\%)}$$

The monthly CTV utilisation percentages of the analysed wind farms are included in Appendix I.2. The overall mean CTV utilisation is around 87%. This utilisation is used in the CTV Demand Model.

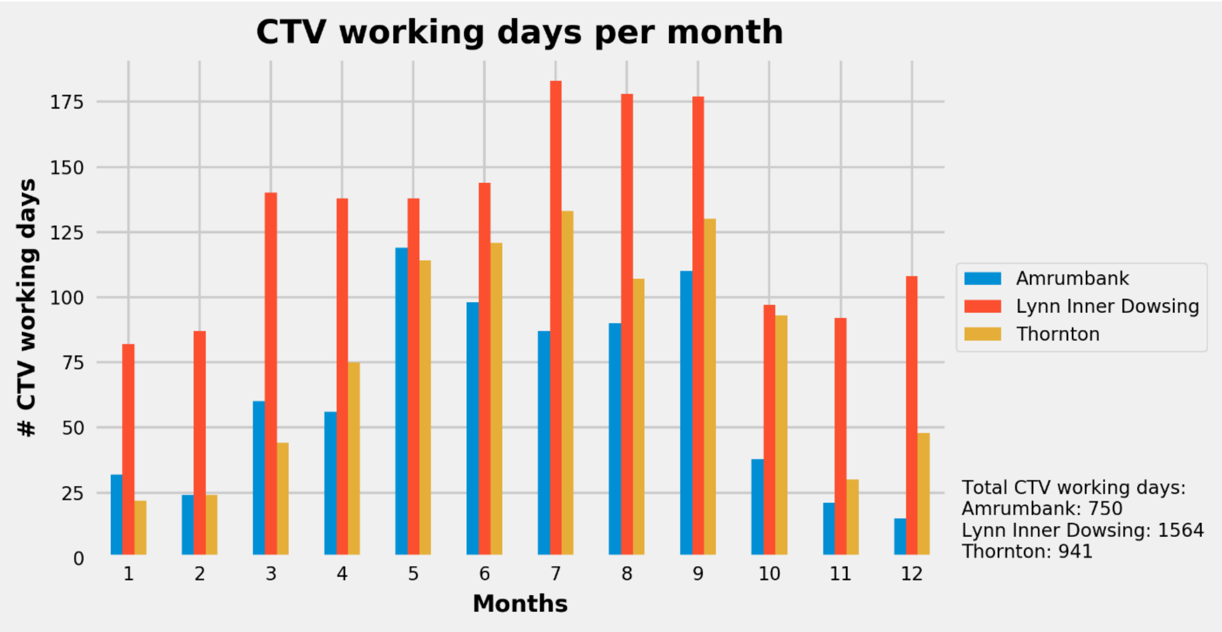

Figure 36: CTV working days per wind farm for the year 2016. Source: own composition.

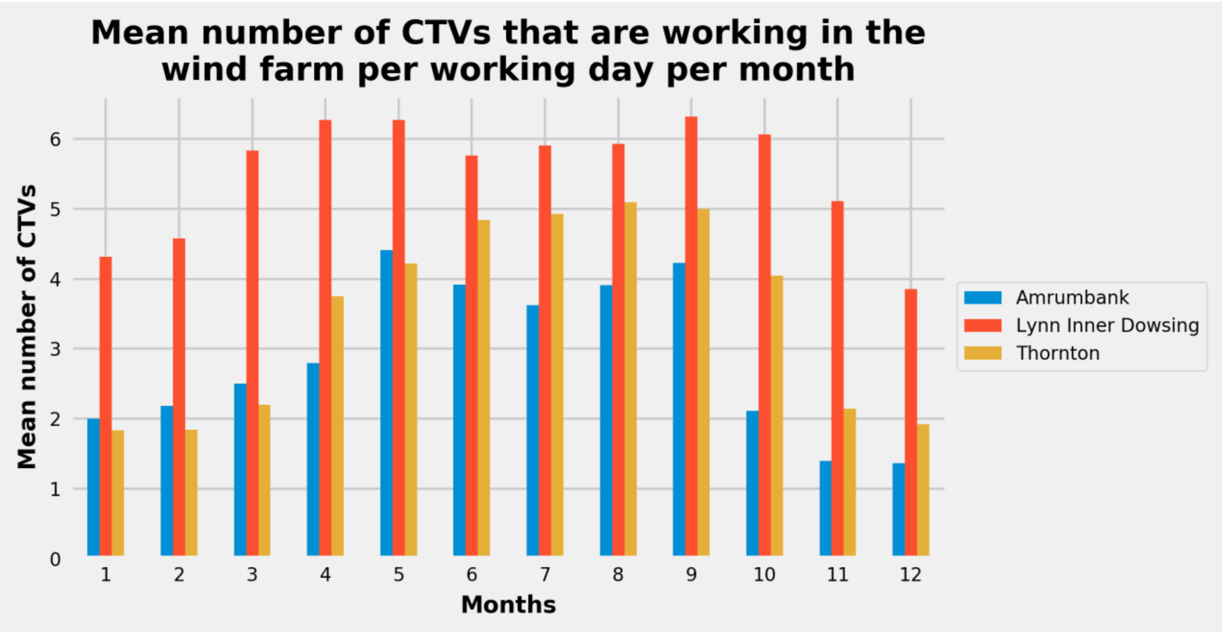

Figure 37: Mean number of CTVs active on working days per wind farm over the year 2016. Source: own composition.

7.2.2.2 Utilisation based on sailing days

Another method to calculate the CTV utilisation is to examine the ratio of sailing days to non-sailing days. Non-sailing days are defined as days on which the maximum SOG is below 1.0 kts, and sailing days are defined as days on which the maximum SOG is above 1.0 kts. The average ration of these two is illustrated in Figure 38 (a) for all the analysed CTVs for the year 2016 (including the periods that the CTVs where not under contract in one of the three analysed wind farms). Based on this figure, it can be concluded that the CTVs sailed on 64% of the days.

Figure 38 (b) shows the average ratio of wind farm access days to non-access days for all three analysed wind farms for the year 2016. An access day is defined as a day for which the Hs was below 1.5 m between 6am and 6pm. On average, the three analysed wind farms where accessible on 73% of the days. This means that on average, the CTVs sailed on 87.8% of the access days. This number is nearly the same as the utilisation calculated with the previously presented method that only focused on the vessels that where under contract in the analysed wind farms.

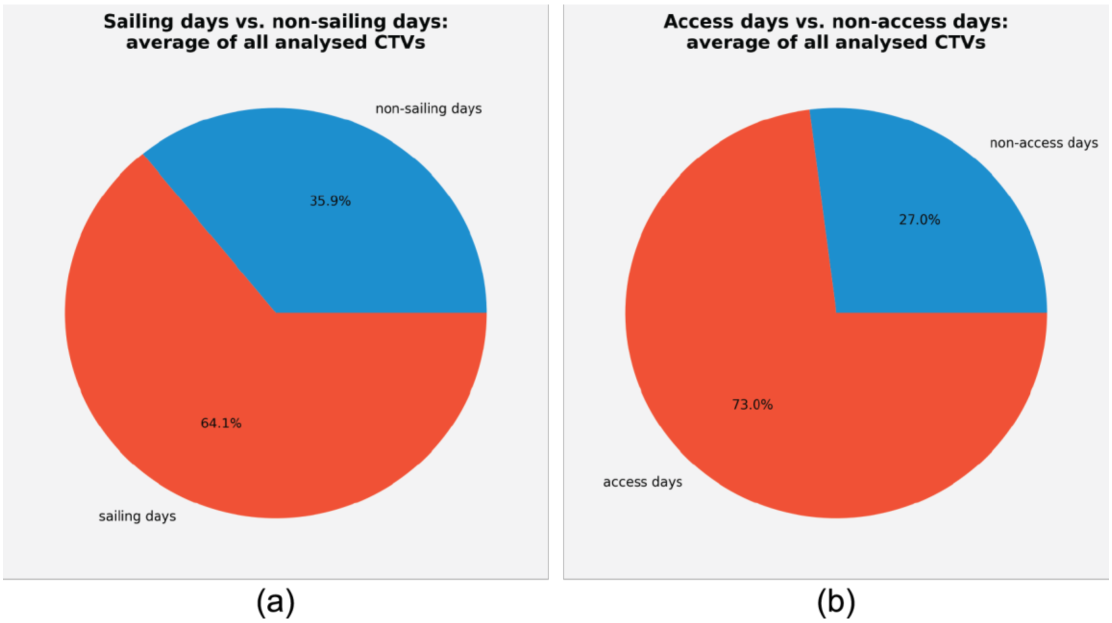

Figure 38: (a) sailing days versus non-sailing days. (b) wind farm access days versus non-access days. Source: own composition.

4C Offshore (2016) observed a large number of CTVs and found that these vessels were 80% of the days operational. This is slightly lower than the 87% found in this study. This difference may be caused by the used methodology. The first method of this study only focused on the periods for which the vessels are under contract to work for the wind farm. Of course, this is not always the case as vessels could be temporarily out of the running for maintenance, refit, etc. Furthermore, the analysed CTV population may have had an above average utilisation in 2016.

7.3 Port Visits

The time between leaving the port in the morning and coming back to the port in the evening is the working time on a CTV working day. A histogram of the working time is depicted in Figure 39. As can be seen, CTVs work normally between 9.5 and 11.5 hour. Barring some time for preparations, mooring and manoeuvring in the port, this is in line with the expectations since most offshore workers work in shifts of 12 hours as is mentioned in Appendix C.2.

Similar histograms as shown in Figure 39 are generated for each month of 2016. These monthly distributions are used to simulate the length of a working day in the CTV Demand Model.

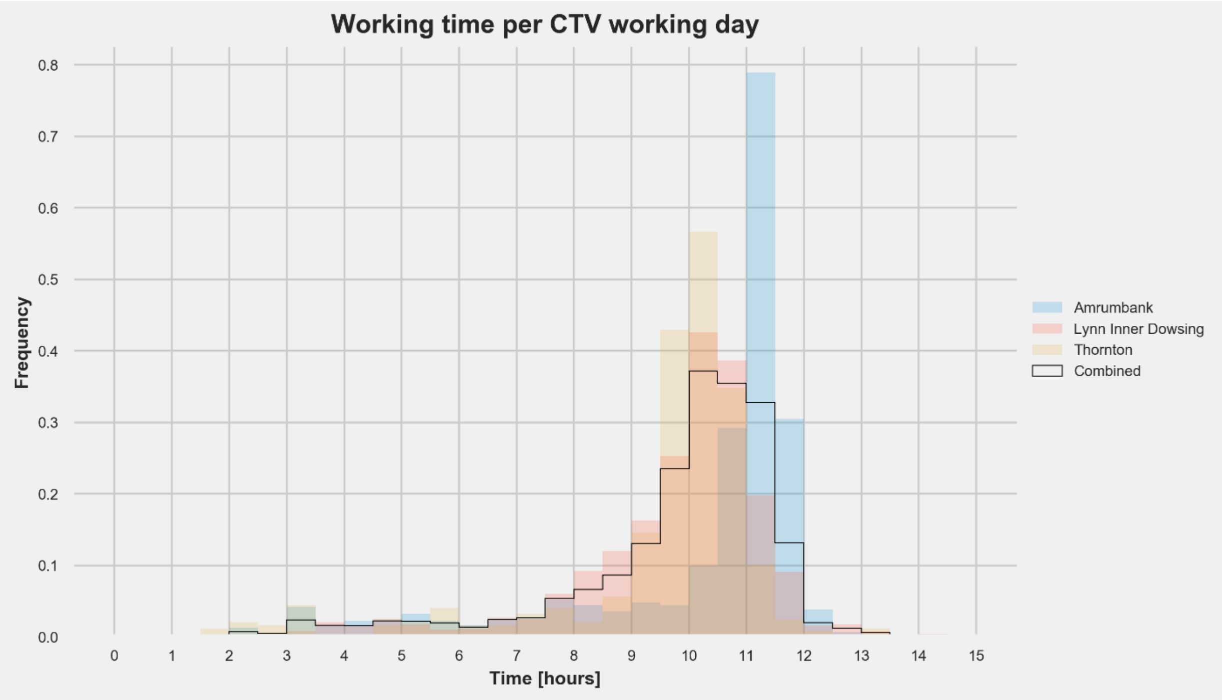

Figure 39: Distribution of time between port exit and port entry on CTV working days in 2016. Source: own composition.

7.4 Transits

The mean SOG of all transits is calculated, and plotted against the Hs (of the centre of the wind farm) at the time that the transfer started (either from port or from wind farm). This results in a cloud of data points that is show in Figure 40. As can be seen in the figure, the mean SOG during transits is normally between 15 and 25 kts. Furthermore, most transits are conducted in sea states below 1.5 m Hs, which is in line with the earlier presented statistics of the wind farm days.

The shown trend line representing the mean SOG as a function of the Hs is used to calculate the required transit time from the port to the wind farm and vice versa in the CTV Demand Model. For this purpose, the dotted stepwise trend is used to determine the means SOG based on the daily Hs. As expected, the mean SOG decreases when the Hs increases. When plotting a separate trend line for the data points from the 7 Damen FCS 2610 vessels, however, the line is more horizontal meaning that the effect of the Hs is less detrimental to the mean SOG for these vessels.

Figure 41 shows that the mean SOG for transits from the port to the wind farm and vice versa are practically distributed the same. Therefore, there is no differentiation made between the two transit types in the CTV Demand Model. As can be seen in the figure, the number of port and wind farm transits are different. This may be caused by outlier removal and/ or CTVs coming from or going to a different port.

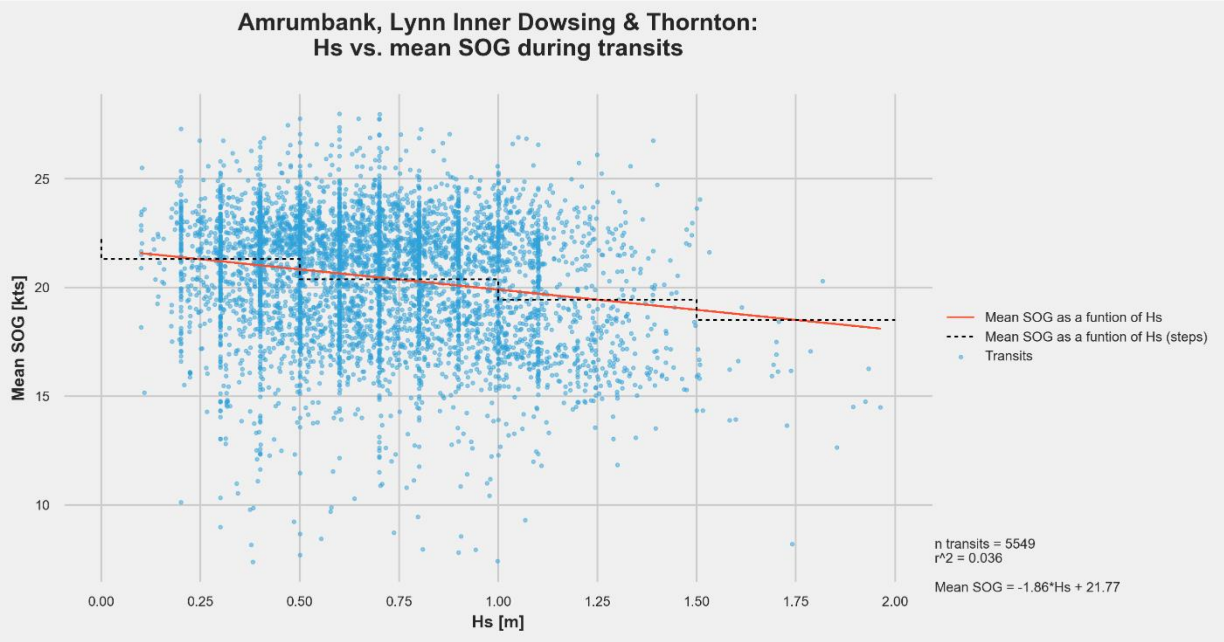

Figure 40: Mean SOG as a function of Hs. Source: own composition.

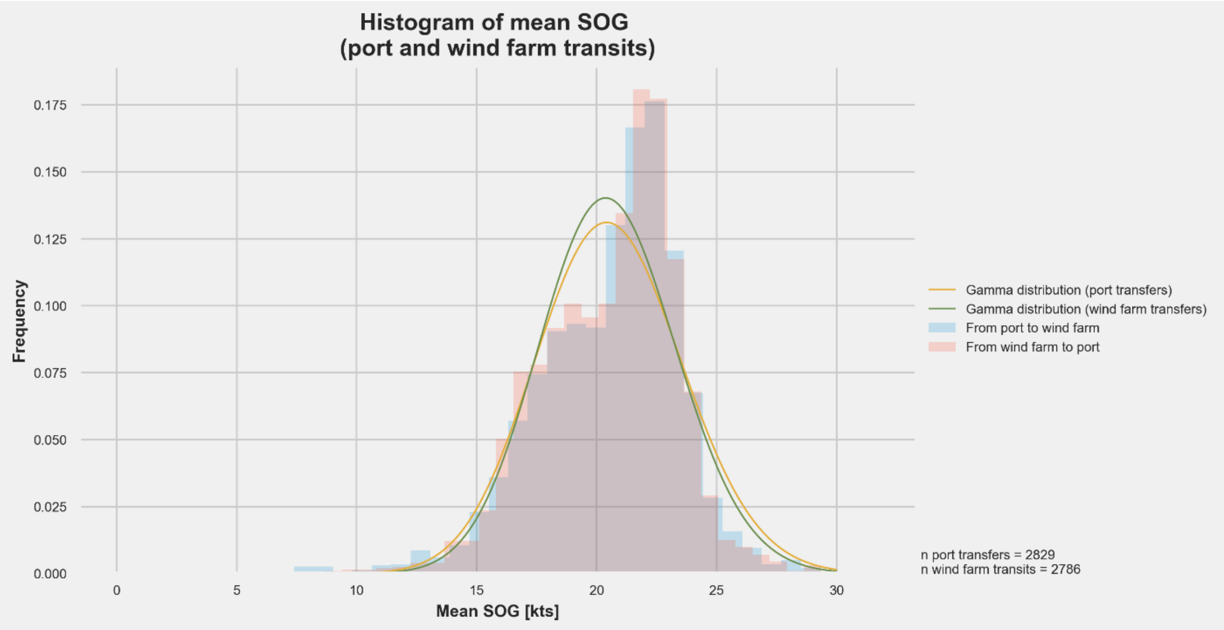

Figure 41: Mean SOG for port and wind farm transits. Source: own composition.

7.5 Operational Profile of Crew Transfer Vessels

The used data contains much more information than is required for the CTV Demand Model and can be presented in this thesis. Information about e.g. the operational profile of CTVs can be of great value for the design proposal of a new vessel. One of many examples is presented in this section.

Figure 42 is a histogram of the SOG of the in-field AIS data of all the CTVs included in this analysis. Note that the histogram represents the number of AIS reports with a certain SOG instead of the sailing time per speed range. There is minor difference between the two, since the AIS frequency is not constant over time. Nonetheless, it is clear from the histogram that CTVs are sailing the majority of the time below 2 kts when they are in the wind farms.

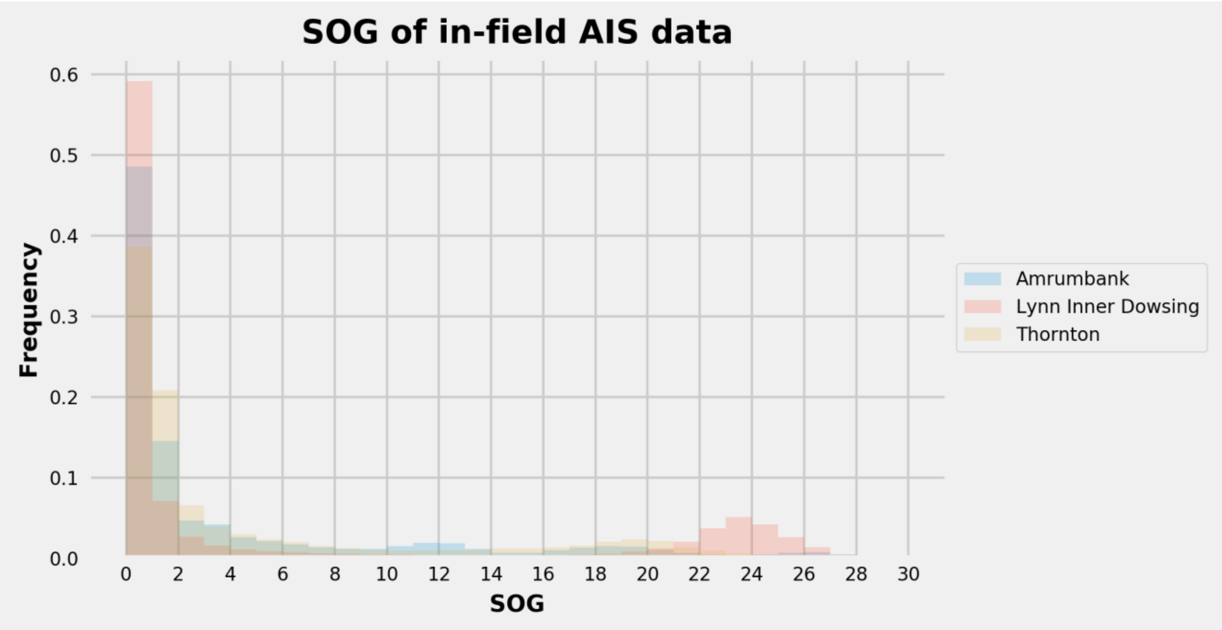

Figure 42: Histogram of the SOG of in-field AIS data. Source: own composition.

The in-field speed profile is interesting for the engineering of among others the propulsion system. At first sight, this profile seems suitable for hybrid propulsion systems. However, what cannot be seen in this histogram is the fact that CTVs require a high propulsion power during transits to push the bow to the turbine (low speed – high power). Still, a hybrid solution may be beneficial since the mean number of CTOs is only around one per hour, which means that there is still plenty of time spent in a low speed – low power modus. This is an example of one of the many applications for which AIS data can be used.

The results obtained from the data mining process are presented and discussed in this chapter. Aforementioned, the presented results are essential input for the CTV Demand Model. The logic of this model is discussed in het next chapter.

8 Crew Transfer Vessel Demand Model

The CTV Demand Model is presented in this chapter. This model can be used to gain insights into the number of required CTVs to execute CTOs for a given wind farm. First is the CTO process summarised to make clear what the outlook is and how this can be modelled. Thereafter, the model output and input are discussed, followed by the model assumptions and logic. The last three sections of this chapter are the model results, validation and sensitivity analysis.

Aforementioned in the introduction, for this project an methodology is used whereby the data is analysed before the model is composed. This is done because of the novelty of AIS data analysis, i.e. it was not known beforehand which information could be obtained from the data.

8.1 Crew Transfer Operation Process

The CTO process is discussed in several parts throughout this thesis. In this section, the process is once more highlighted because it is essential to understand the CTV Demand Model.

The outlook of a regular CTV day is as follows; in the morning, the CTV sails from the port/ offshore maintenance hub to the wind farm to drop off technicians at several turbines. Whenever the technicians finished their tasks on a turbine, the CTV picks them up and brings them to the next turbine. After picking up/ dropping off technicians at a turbine, it may also happen that the CTV must wait until the technicians finished their tasks on the turbines. In this case, the CTV is idle and generally drifts around until the technicians are done. This process continues till the end of the day/ shift, thereafter the CTV sails back to the port/ offshore maintenance hub.

CTVs are mostly used to service wind farms that are relatively close to the shore, since the transit time consumes a lot of valuable in-field working time. When wind farms are located further from the shore, strategies with offshore maintenance hubs and SOVs are becoming more attractive to decrease the transit time. Furthermore, CTVs may not be suitable for areas with severer sea states, since the operation is limited to 1.5 m Hs. This weather window is also the reason why the planned maintenance is normally carried out during summer campaigns. As a result of these summer campaigns, the CTV demand is much higher in the summer relative to the winter.

Not mentioned before; CTVs often service multiple wind farms that are from the same owner/ have the same O&M agreements (4C Offshore, 2016). These CTVs are used for the grouping of maintenance activities/ to cover short peak demands. This is also the case for the three wind farms Lynn, Lincs and Inner Dowsing that are considered as one wind farm in this project because they have common borders. As can be seen in Appendix C.1, most CTVs working here are under contract for all the three wind farms.

8.2 Model Output & Input

The desired output of the CTV Demand Model is the number of CTVs required to service a given (future) offshore wind farm in terms of CTOs. Notice that the output is the number of CTVs that should be under contract for the wind farm, and that the vessels are normally not 100% of the time under contract. The specifications and parameters from both the wind farm and the CTV/ CTO process that are listed underneath are used to model the CTV demand. It is explained in a latter section of this chapter how these specifications and parameters are used.

From the wind farm:

- Distance between the wind farm and the port/ offshore maintenance hub in nautical miles. This is used to calculate the required transit time.
- Hs probability distribution of the wind farm per month. The Hs is among others used to simulate whether the wind farm is accessible or not.
- CTO demand distribution per turbine per year, which is used to simulate the CTO demand for all the turbines in the wind farm.
- Number of turbines. This is used to simulate the total CTO demand of the wind farm.

From the CTV/ CTO process:

- Distribution of the number of transfers that can be executed per hour. This is used to simulate the daily CTO supply.
- Distribution of the length of the working day. The time between leaving and entering the port is needed to model the in-field time. A different distribution is used for each month, as the working days may be longer during the summer campaigns.
- The trend line in the scatter of the mean SOG and Hs presented in section 7.4 is used to simulate the required transit time per day. This time, together with the length of the working day determines the time-slot in which the CTOs should be executed.
- The maximum Hs in which the CTOs can be executed. This is used to determine whether the wind farm is accessible or not. The default value is 1.5 m.
- The CTV utilisation is used to simulate the number of operational days. The default utilisation is 87%.

8.3 Model Assumptions

When making a model, it is unavoidable to make assumptions to simplify the reality. The most significant assumptions made for the CTV Demand Model are discussed in this section. The assumptions are presented from having the greatest relative importance to the least relative importance.

The first assumption is that the number of operative CTVs is assumed to be constant over each month. In reality, this is not always the case as some CTVs are e.g. deployed for just one week or even a single day. Because the CTV demand is modelled on a monthly level, the output demand is the monthly average.

The model is also tested on a weekly basis to get more precise results for the short peaks, however, this gave inconsistent and wrong results. The reason for this is that the CTO demand is not correlated to the Hs probability distribution in the model, while this is indirectly the case in reality. In the model, it may happen that the Hs > 1.5 m for a whole week, meaning that no CTOs can be executed. There still is a CTO demand modelled for that week, since this is not correlated to the possibility to supply CTOs. In reality, the CTO demand would then increase in the week before (based on weather forecasts) and/ or the week after the non-access week. When modelling on a monthly level, the effect of this problem is less decisive because it is levelled out over a longer period.

A second assumption is that working days are identical for all CTVs. E.g. on the first of August, the length of the working day, the transit time, the number of transfers and the number of operational days are all the same for each CTV. For the second of August, a new day is simulated that is again the same for all the CTVs, etc. Off course, this is in reality not the case. This assumption is made to simplify the model and to shorten the computing time, since otherwise many more working days should be simulated.

Third, the CTVs are assumed to be operational for 87% of the days as is explained in section 7.2.2. Furthermore, the non-operational days are assumed to be equally distributed over the months. In reality, the CTV availability differs between months. There is no clear winter – summer trend, e.g. in Amrumbank the lowest and highest availability are in the months October and November. To simplify the model, the availability is kept constant over the year. The effect of this is that the CTV demand results may be too low/ high for certain months, however, the yearly average is expected to be unaffected.

Last, the CTO parameters may differ between the summer and winter, as well as for different maintenance strategies. It may for example be the case that summer months are used for long planned maintenance tasks while in the winter only short responsive tasks are executed to keep the turbines running. Both tasks may require different CTO parameters. In the model, however, the same distribution function for the CTOs that can be executed per hour is used throughout the whole year. The other probability distributions, Hs and the length of the working day, are given per month. The effect of this is that for some months the CTO supply of one CTV may be a bit too high/ low, however, the yearly average is expected to be unaffected.

8.4 Logic of the Model

The starting point for the CTV Demand Model is an analysis of the CTO process, and the model is developed via a continuous/ feedback-loop process (similar to the data mining algorithms). The logic of the model is described in this section, and the model steps are illustrated in the flowchart in Figure 43.

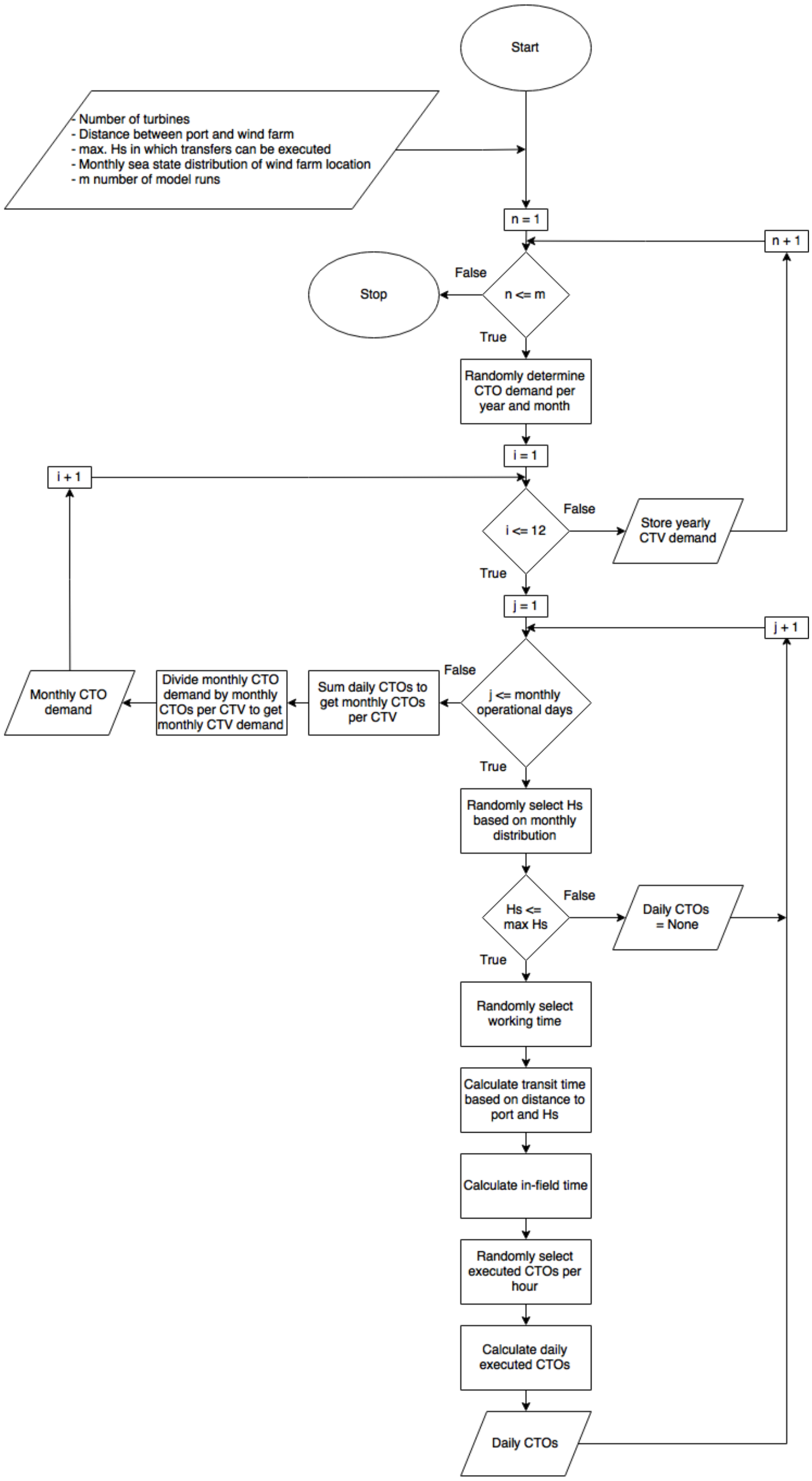

Figure 43: Flowchart of CTV Demand Model. Source: own composition.

The model is written in the Python programming language, and makes use of parameters that are randomly selected based on probability distributions. Therefore, the Monte Carlo method is used to obtain the results. As can be seen in Figure 44 the outcome of the model is more or less constant from 1000 model runs and over. The model process should therefore be repeated at least 1000 times to get reliable results. Running the model 1000 times takes around 2-3 minutes.

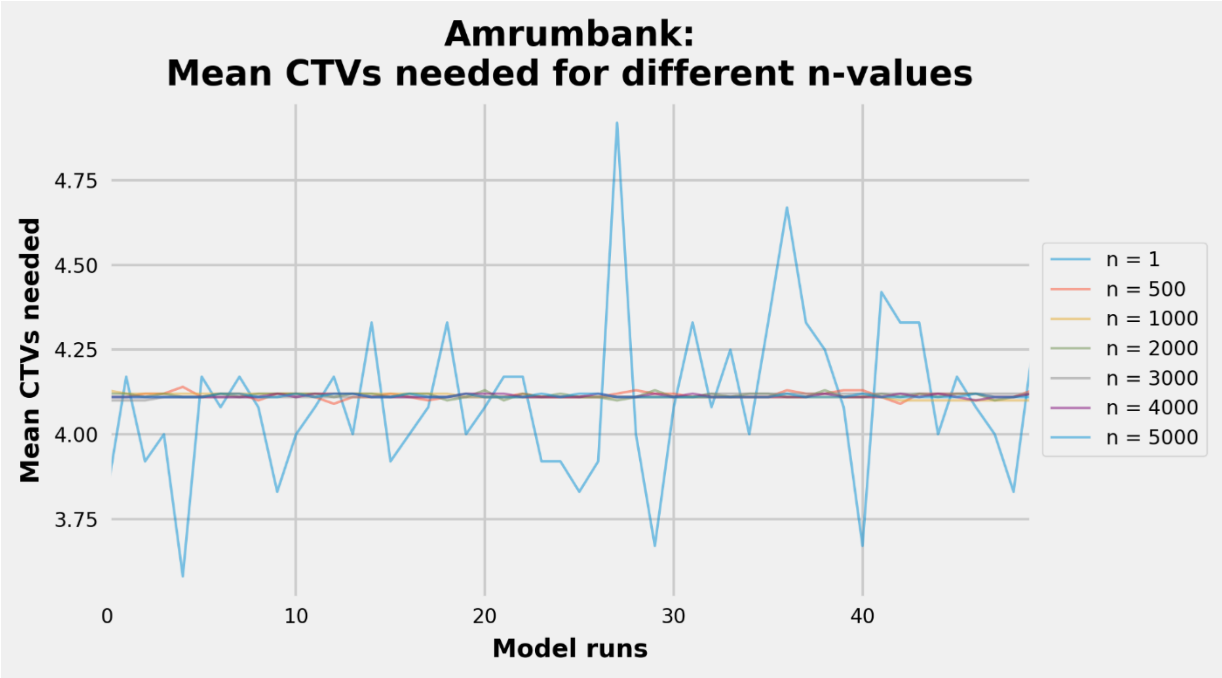

Figure 44: Model results for different n-values. Source: own composition.

8.4.1 Crew Transfer Operation demand

The CTO demand is simulated for each turbine in the wind farm individually, and is randomly selected based on the distribution of CTOs per turbine per year that is shown in section 7.1.1. For e.g. a wind farm with 100 turbines, this results in a list with 100 yearly CTO demands. The sum of this list is the total yearly CTO demand of the whole wind farm. Aforementioned, the CTO demand is not constant over the year as there is a peak demand in the summer period due to planned maintenance. Therefore, the total yearly CTO demand is divided into monthly demands as is explained in section 7.1.1.2 to deal with these peaks.

The CTO demand distribution is the model input variable that determines the number of CTOs that are executed per year. As is shown in section 7.1.1, the CTO demand varies significantly between wind farms. Therefore, the accuracy of the model will be better when a CTO demand distribution close to the actual CTO demand of the wind farm is used. However, the specific CTO demand distribution is not always known. For the CTV Demand Model three different CTO demand distributions can be used, which are elaborated in the following. The model results are presented in the next section for all three distributions.

- **General CTO demand distribution** is the average distribution of the three analysed wind farms together (Amrumbank, Lynn Inner Dowsing and Thornton). This distribution is used to analyse the market as a whole/ for wind farms for which the specific CTO demand distribution is unknown.
- **Own CTO demand distribution** is the distribution corresponding to each individual wind farm, i.e. the own CTO demand distribution of Amrumbank is derived from the CTOs executed in Amrumbank only. Meerwind Sud/Ost and Sheringham are not analysed, so they do not have their own CTO demand distribution. This distribution is used to get more accurate results for individual wind farms.
- **Siemens CTO demand distribution** is the average distribution of the wind farms that are equipped with Siemens SWT 3.6 MW turbines (Amrumbank and Lynn Inner Dowsing). Thornton is the only wind farm of the five that is not equipped with the same Siemens turbines, and therefore excluded. This distribution is used for one specific wind farm category: those equipped with Siemens SWT 3.6 MW turbines.

8.4.2 Crew Transfer Operation supply

As mentioned in the previous part, the CTO demand is simulated per month. Therefore, the CTO supply should be simulated per month as well. The monthly CTO supply is the same as the sum of the daily CTO supplies, which are simulated with the model.

For each operational day in the month is the CTO supply of one CTV simulated (87% of the days are operational days as is explained in section 7.2.2). The daily CTO supplies are then summed to calculate the monthly CTO supply for this one CTV. E.g. in January the daily CTO supply is simulated 27 times (≈ 31 days * 87%). The sum of these 27 CTO supplies is then the total monthly CTO supply of one CTV in January.

The following steps are repeated for each operational day to simulate the CTO supply of one CTV:

1. Randomly simulate the daily Hs based on a sea state probability distribution table. For each month is a different probability distribution table used, since the sea states are severer in the winter months.
2. If the Hs > 1.5 m: no CTOs are executed since the wind farm is inaccessible.
3. If the Hs =< 1.5 m: the CTO supply is modelled via the following steps:
    a. Randomly select the length of the working day based on the month-specific probability distribution function of the working time per CTV day (see section 7.3 for the distribution).
    b. Calculate transit time. The transit time is a function of the wind farm to port distance and the means SOG. The latter is a function of the Hs (see section 7.4).
    c. Calculate the in-field time. This is the length of the working day minus two times the transit time.
    d. Randomly select the number of CTOs that can be executed per hour. This is selected based on the probability distribution of CTOs per hour (see section 7.1.2)

e. Calculate the daily CTO supply by multiplying the CTO per hour rate with the in-field time. This number is rounded to the nearest integer to get the CTO supply for one CTV on one day.

This process is repeated for each operational day in the month to calculate the total monthly CTO supply of one vessel, and is then repeated for each month in the year.

8.4.3 Compare Crew Transfer Operation demand with supply

The total monthly CTO demand and the monthly CTO supply of one CTV are simulated via the methods described in the previous two sections. The last step of the model is to compare the CTO demand with the CTO supply. The mean monthly CTV demand is calculated by dividing the monthly CTO demand by the monthly CTO supply of one CTV. The monthly CTV demand is not rounded to whole integers, as this gives better overall results of the model.

Now the logic of the CTV Demand Model is clear, the remaining of this chapter focuses on the model results, validation and sensitivity analysis. The results are given for 5 offshore wind farms, of which three are the used input wind farms. The model is validated based on the AIS data to get an idea of the accuracy of the model, and the sensitivity analyses is performed to gain insights into the effect of some input parameters.

8.5 Model Results

The model results are shown in Table 16. The figures are the yearly average CTV demand per wind farm and per used CTO demand distribution. Apart from the three analysed wind farms are the model results of two other wind farms presented: Meerwind Sud/Ost and Sheringham. These two wind farms are equipped with the same Siemens STW 3.6 MW turbines as Amrumbank and Lynn Inner Dowsing.

Table 16: Model results - yearly average CTV demand for different CTO demand distributions per wind farm. Source: own composition.

	General CTO demand distribution	Own CTO demand distribution	Siemens CTO demand distribution
Amrumbank	4.22	3.78	3.77
Lynn Inner Dowsing	5.83	5.19	5.23
Thornton	2.35	3.32	-
Meerwind Sud/Ost	3.85	-	3.44
Sheringham	3.29	-	2.93

Table 16 shows the yearly average CTV demand. However, the CTV demand is not constant over the year. The monthly average CTV demand for Meerwind Sud/Ost and Sheringham are presented in Figure 45 and Figure 46. In these figures can be clearly seen that the CTV demand is higher during the summer campaign than during the winter months. In these figures is the average monthly CTV demand highest for the month September, which is therefore the peak demand. Similar figures for Amrumbank, Lynn Inner Dowsing and Thornton are included in the model validation section.

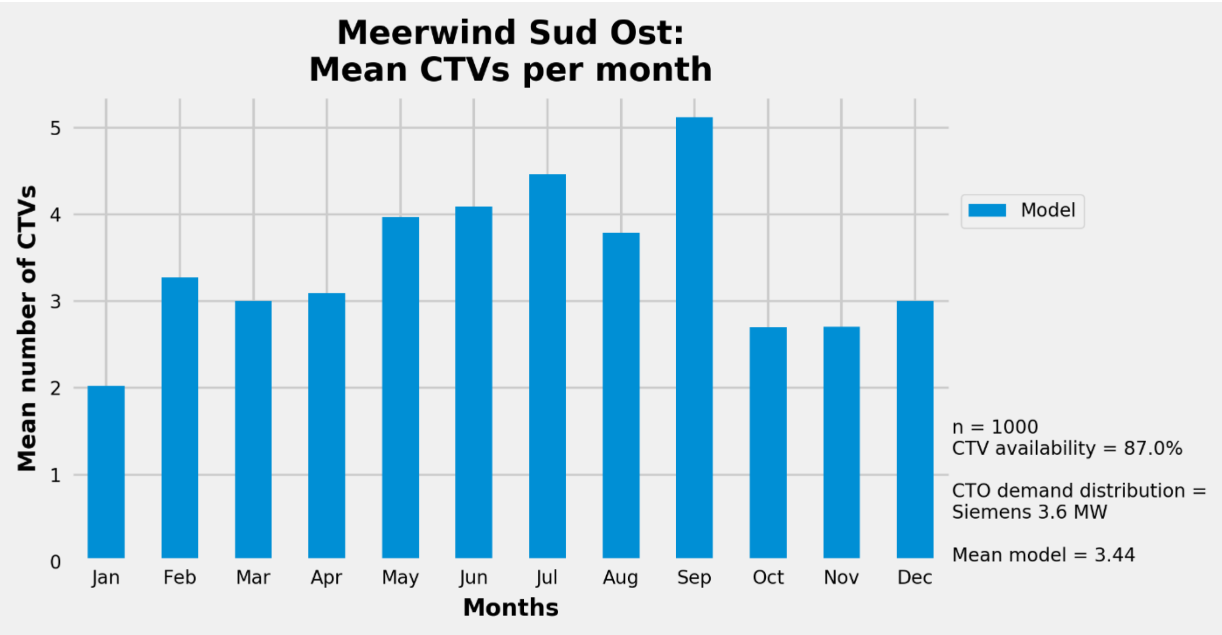

Figure 45: Model results – monthly average CTV demand for Meerwind Sud/Ost. Source: own composition.

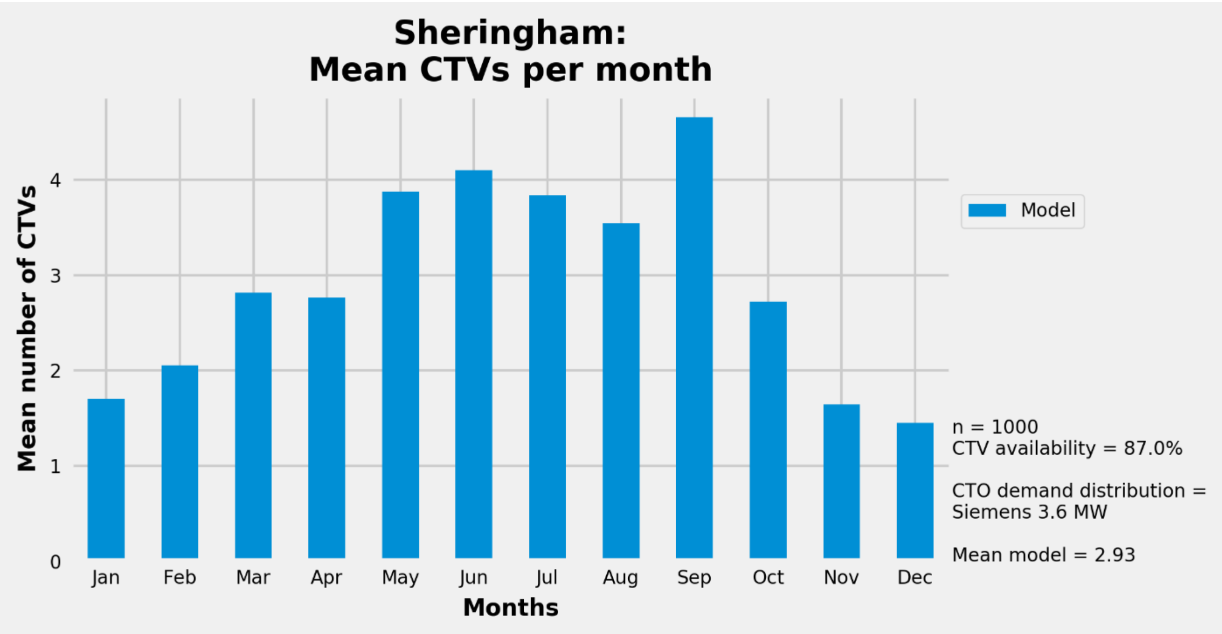

Figure 46: Model results – monthly average CTV demand for Sheringham. Source: own composition.

8.5.1 Crew Transfer Vessel demand per number of turbines

The model results are presented in Table 17 as the required number of CTVs per X turbines per year. The results are presented in this format to enable comparing the model results with 4C Offshore (2016), who state based on a more simplistic AIS analysis that the CTV market size is 1 vessel per 15.34 turbines per year. The comparison is made in the model validation section of this chapter.

The presented numbers are composed based on the yearly average CTV demand and the peak CTV demand. The peak demand is the highest monthly average CTV demand (the demand for the month September in Figure 45, Figure 46, Figure 47, Figure 48 and Figure 49). Evidently, the CTV market size is larger than the yearly average as the peak demand must be met. Note that the presented model results are for the Siemens CTO demand for all wind farms but Thornton. For Thornton are the results for its own CTO demand used, since Thornton is the only wind farm with Senvion turbines instead of Siemens SWT 3.6 MW turbines.

Table 17: Model results – CTV demand (yearly average & peak) presented as 1 CTV per X turbines. Source: own composition.

		Yearly average CTV demand		**Peak CTV demand**	
	Turbines	Model Results	1 CTV per X turbines per year	Model Results	1 CTV per X turbines per year
Amrumbank	80	3.77	21.2	5.59	14.3
Lynn Inner Dowsing	129	5.23	24.7	8.41	15.3
Thornton	54	3.32	16.3	5.24	10.3
Meerwind Sud/Ost	80	3.44	23.3	5.09	15.7
Sheringham	88	2.93	30.0	4.69	18.8
Average			**23.1**		**14.9**

8.6 Model Validation

In this section, the model is validated based on two different methods: The results are validated based on AIS data; and the model results are compared with the figures from 4C Offshore.

8.6.1 Model results vs. Automatic Identification System data

The mean number of CTVs working in the wind farm on working days is counted via the AIS data. In Table 18 are these figures compared with the model results to validate the accuracy of the model. The model results are shown for the three earlier explained CTO demand distributions, and the shown percentages are the difference of the model results with the AIS data. Furthermore, Figure 47, Figure 48 and Figure 49 show the AIS- and model results on a monthly level.

Table 18: Validation of the model results (yearly average CTV demand) based on the average number of CTVs working in the wind farm (counted via AIS data analysis). Source: own composition.

	AIS	Model Results – yearly average CTV demand		
	Yearly average CTVs working in the wind farm	General CTO demand distribution	Own CTO demand distribution	Siemens CTO demand distribution
Amrumbank	2.87	4.22 / +47%	3.78 / +32%	3.77 / +31%
Lynn Inner Dowsing	5.52	5.83 / +6%	5.19 / -6%	5.23 / -5%
Thornton	3.48	2.35 / -32%	3.32 / -5%	-
Total	**11.9**	**12.4 / +4%**	**12.3 / +3%**	**9.0 / +7%**

For Amrumbank, the model results are significantly higher for all three the CTO distributions. There are multiple reasons for this. First, the CTOs executed per hour is slightly higher for Amrumbank than for the other two wind farms as is shown in section 7.2.2. Secondly, the length of the working days in Amrumbank are relatively long as depicted in section 7.3. Third, the average CTV availability in Amrumbank was around 95% in 2016, which is much higher than the used 87% (see Appendix I.2). So, the CTVs executed more CTOs per hour, worked more hours per day and worked on more days that the average CTV. Evidently, this results in a lower number of required CTVs.

The result for the General CTO distribution is a bit too high for Lynn Inner Dowsing. This is due to the fact that the CTO demand for Lynn Inner Dowsing is lower than the general demand. For the Siemens CTO distribution, however, the result is quite good. It is slightly lower than the actual mean number of CTVs that worked in the wind farm, which can be explained by the fact that the CTV availability in Lynn Inner Dowsing was 6 percent points lower than the availability used in the model (see Appendix I.2).

When zooming in on a monthly level, the CTV demand is less good (see Figure 48). This is because the model works with a summer peak CTO demand. In Lynn Inner Dowsing the sea state conditions are quite constant over the whole year due to its geographical location. This results in the fact that the CTOs are levelled out over the months more evenly in Lynn Inner Dowsing than in the other wind farms, and that the summer peak is less present.

The model results for Thornton's own CTO distribution are still slightly too low, which is due to the fact that the working days of the CTVs operative in Thornton are the shortest of all three wind farms (see section 7.3). When using the general CTO demand distribution, the model results are not very good. This is caused by the fact that the CTO demand is 159 transfers per turbine per year on average, whereas this is around 113 for the general CTO demand distribution as is shown in section 7.1.1.

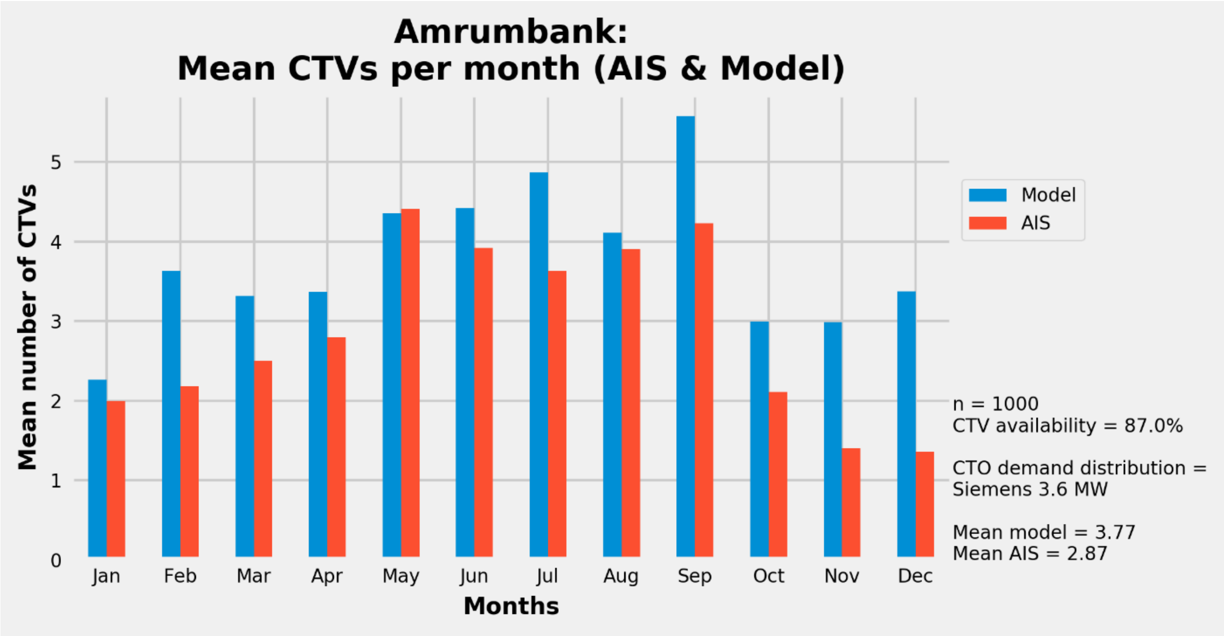

Figure 47: Monthly average CTV demand (model results and AIS analysis) for Amrumbank 2016. Source: own composition.

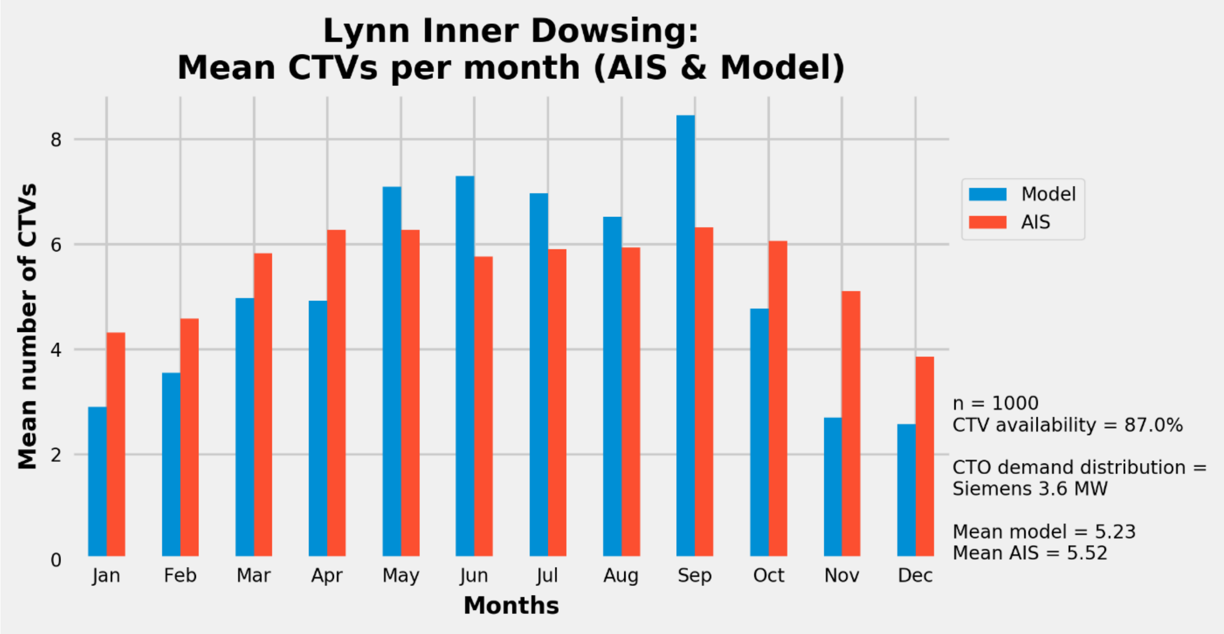

Figure 48: Monthly average CTV demand (model results and AIS analysis) for Lynn Inner Dowsing 2016. Source: own composition.

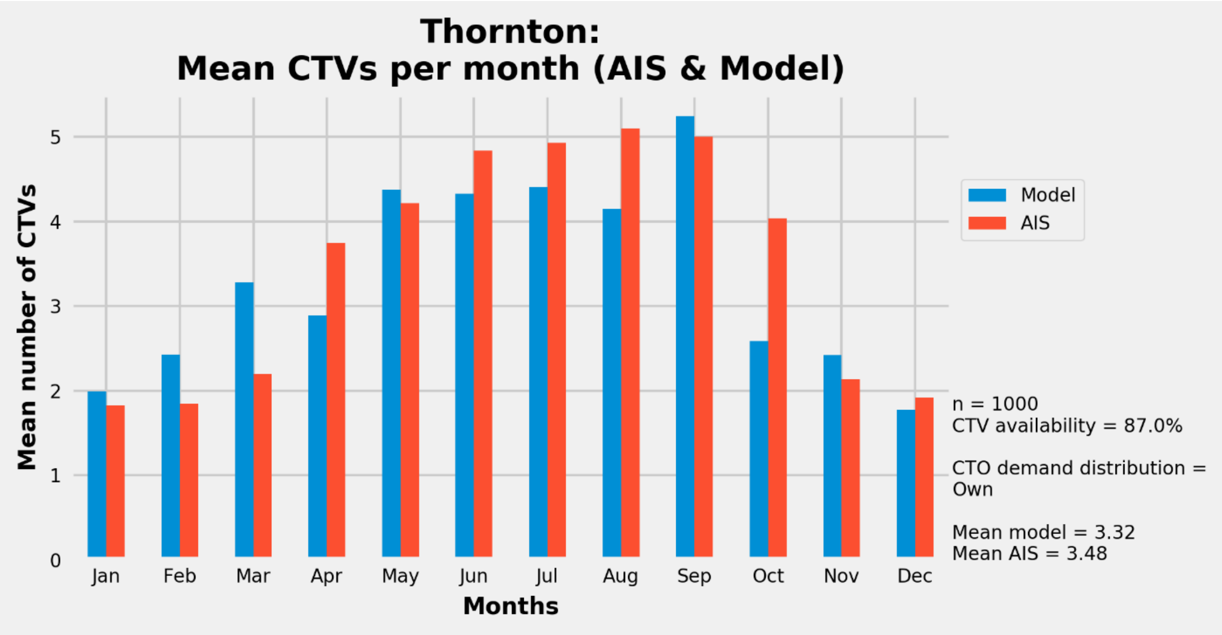

Figure 49: Monthly average CTV demand (model results and AIS analysis) for Thornton 2016. Source: own composition.

As can be seen in Table 18 and Figure 47, Figure 48 and Figure 49, the model results are not exactly the same as the results from the AIS analysis for each individual wind farm. Therefore, the CTV Demand Model is more suitable to determine the overall demand (of a cluster of wind farms), than to precisely determine the CTV demand of individual wind farms. In the following part is explained why the accuracy of the model flaws.

There are a lot of vital factors that influence the CTV demand. These factors cannot (always) be set in the model, resulting in inaccurate results for especially individual wind farms. To illustrate this, two examples are given; one for a human- and one for a technical factor.

The working time may differ between offshore service companies, maintenance contracts, collective employment agreements, etc. In Amrumbank, the time between leaving the port in the morning and entering the port in the evening is mostly between 11.0 - 11.5 hours, whereas this is between 9.5 - 10.5 hours in Thornton. On a yearly basis, this is a difference of around 290 working hours per used CTV (80% CTV utilisation and 80% access day). So, this human factor has a significant influence on the total CTV demand.

A direct influencing technical factor is the CTO demand of the wind turbines. The CTO demand of Thornton is about 50% higher than the demand of Amrumbank and Lynn Inner Dowsing. Since the CTV demand is 1:1 correlated to the CTO demand, this factor has a major influence on the required number of vessels.

The effect of vital factors may be diminished by implementing more input parameters. The CTV Demand is now only modelled based on the number of turbines, sea state distribution and distance between port and wind farm. Adding more wind farm specific input variables may make it possible to model the CTV demand more accurate. It may, however, not be desirable to make the model more complex than is strictly necessary. Furthermore, the required information of wind farm specific parameters may not be available. For these reasons, the extra input factors should be selected in such a manner that the model results are fit for purpose, without making it too complex/ demanding too much resources.

Not only between wind farms, but also between months may variables vary. In the model, however, not all input variables are given per month. An example of this can be seen when comparing the model results with the AIS analysis for September in Figure 47, Figure 48 and Figure 49. The model demand is in all three cases higher than the AIS analysis, which is strange at first sight since the model demand is based on the monthly executed CTOs that are counted with the AIS data. However, there may be a logical explanation for this. September is close to the end of the summer maintenance campaign as the sea states are becoming severer in fall. All the planned maintenance tasks that should be finished before winter. So, if the operator is behind schedule, the CTVs may work above average hard, meaning that they execute more transfers per hour, are less idle, etc. If this is the case, more CTOs can be executed with less CTVs. When further developing this model, it is recommended to use input variables that vary per month to get more accurate results for each month.

The previous part explained why the model is not accurate for individual wind farms and months. This section will explain why the model is not (yet) accurate for the entire market. The input parameters of the CTV Demand Model are derived from the analysis of 39 CTVs that served 3 offshore wind farms over the course of 2016. Evidently, it cannot be assumed that the parameters derived from these three wind farms are the market averages. To get more accurate model results for the entire CTV market, more CTVs and wind farms should be analysed. Adding more wind farms requires relatively little resources, as the method is already developed. Especially if the current method can be automated by software developers.

8.6.2 Model results vs. figures from 4C Offshore

4C Offshore (2016) conducted a research into the CTV demand based on AIS data as well. They counted the number of vessel days for 26 wind farms in Europe over the course of 2015. Based on this research they state that the CTV market size for O&M activities is 1 vessel per 15.34 turbines. Although not clearly described, it is expected that this number is based on the peak demand during the summer campaign. A selection of the results of 4C Offshore is depicted in Table 19.

Table 19: Research results adopted from 4C Offshore (2016). Used CTV utilisation rate is 80% and used data is from 2015.

	Turbines	Vessel days	CTVs needed	1 CTV per X turbines per year
Amrumbank	-	-	-	-
Lynn Inner Dowsing	129	2617	8.96	14.4
Thornton	54	1352	4.63	11.7
Meerwind Sud/Ost	-	-	-	-
Sheringham	88	1371	4.70	15.6
Average				**13.9**

Table 20 shows similar results as Table 17. However, in Table 20 is the average CTV demand calculated based on only those wind farms for which the results of 4C Offshore are known. Based on these results, it can be stated that the CTV market size for O&M activities is 1 vessel per 14.8 turbines. This is 6.5% higher than the 1 vessel per 13.9 turbines stated by 4C Offshore for the same wind farms.

Table 20: Model results (yearly average & peak demand). Used CTV utilisation rate is 87%. Source: own composition.

		Yearly Average		Peak Demand	
	Turbines	Model Results	1 CTV per X turbines per year	Model Results	1 CTV per X turbines per year
Amrumbank	80	3.77	21.2	5.59	14.3
Lynn Inner Dowsing	129	5.23	24.7	8.41	15.3
Thornton	54	3.32	16.3	5.24	10.3
Meerwind Sud/Ost	80	3.44	23.3	5.09	15.7
Sheringham	88	2.93	30.0	4.69	18.8
Average (Amrumbank & Meerwind Sud/Ost excluded)			**23.7**		**14.8**

The 6.5% difference can be caused by multiple factors. First, the research of 4C Offshore is based on data of 2015, this study used data of 2016. Secondly, the vessel days of 4C Offshore may be defined differently that is done for this study. Third, 4C Offshore states that the utilisation rate of CTVs is 80%, meaning that CTVs are available 292 days per year. The used utilisation rate in the CTV Demand Model is 87% as is explained in section 7.2.2. To validate the results, the results of the CTV Demand Model with a utilisation rate of 80% instead of 87% are obtained and presented in Table 21. In this case, the CTV market size for O&M activities is 1 vessel per 13.4 turbines. This is only 3.6% lower than the results

of 4C Offshore for the same wind farms. This difference can be explained by the same two reasons as explained before; different year and possibly different method.

Table 21: Model results (yearly average & peak demand). Used CTV utilisation rate is 80%. Source: own composition.

		Yearly Average		Peak Demand	
	Turbines	Model Results	1 CTV per X turbines per year	Model Results	1 CTV per X turbines per year
Amrumbank	80	4.09	19.6	6.01	13.3
Lynn Inner Dowsing	129	5.66	22.8	9.25	13.9
Thornton	54	3.60	15.0	5.74	9.4
Meerwind Sud/Ost	80	3.73	21.4	5.54	14.4
Sheringham	88	3.18	27.7	5.18	17.0
Average (Amrumbank & Meerwind Sud/Ost excluded)			**21.8**		**13.4**

The model validation based on the AIS data gives a maximum difference of 32% for individual wind farms and 4% for the three wind farms combined. The model is less suitable for individual wind farms due to the large number of variables that determine the CTV demand. When analysing a cluster of wind farms, the effect of these variables is averaged, and therefore less influencing. So, for clusters of wind farms is the model quite accurate. Furthermore, the model results are comparable with those of 4C Offshore.

8.7 Sensitivity Analysis

A sensitivity analysis of the CTV Demand Model is performed to gain more insights into the relation between the input parameters and the model output. This analysis is performed for the Hs limit, the distance between the wind farm and the port, CTV speed and the CTO demand.

8.7.1 Mean significant wave height limit

The weather window of CTOs is a determining factor for CTV demand. The effect of the 1.5 m Hs limit is examined by lowering and raising this limit. The effect of this on the mean number of CTVs required is depicted in the following tables.

Table 22: Sensitivity analysis for the maximum Hs during CTOs for Amrumbank. Source: own composition.

Amrumbank	**1.0 m Hs**	**1.5 m Hs**	**2.0 m Hs**	**2.5 m Hs**
Yearly average CTV demand	Inf.	3.77	3.08	2.85
CTV demand in- / decrease	Inf.	0%	-18%	-24%

Table 23: Sensitivity analysis for the maximum Hs during CTOs for Lynn Inner Dowsing. Source: own composition.

Lynn Inner Dowsing	**1.0 m Hs**	**1.5 m Hs**	**2.0 m Hs**	**2.5 m Hs**
Yearly average CTV demand	6.34	5.23	4.98	4.94
CTV demand in- / decrease	+21%	0%	-5%	-6%

Table 24: Sensitivity analysis for the maximum Hs during CTOs for Thornton. Source: own composition.

Thornton	**1.0 m Hs**	**1.5 m Hs**	**2.0 m Hs**	**2.5 m Hs**
Yearly average CTV demand	4.72	3.32	2.93	2.79
CTV demand in- / decrease	+42%	0%	-12%	-16%

A first note: in Amrumbank, the CTV demand is ‘Inf.’ when the max Hs is 1.0 m, meaning that in some months the wind farm is not accessible, and therefore, the CTO demand cannot be met.

The effect is stronger for Amrumbank and Thornton then for Lynn Inner Dowsing. This is due to the sea state distributions of the wind farms. As illustrated in Appendix B.2, the Hs is rarely above 1.5 m in Lynn Inner Dowsing, whereas this occurs more frequent in Amrumbank and Thornton. So, the effect should be verified per case since it may be more/ less strong for different wind farms.

In reality, the effect may be even stronger than is presented in the tables above. The necessity of summer campaigns to execute the planned maintenance will diminish since the wind farms are accessible for a longer time period if CTOs can for example be executed up to 2.0 m Hs. A result of this is that the summer peak demand for CTOs can be levelled out over a longer time period. Therefore, it is expected that e.g. a reduction of more than 18% in mean CTV demand can be accomplished for Amrumbank if the CTOs can be executed safely in Hs up to 2.0 m.

8.7.2 Distance wind farm to port

The distance between the wind farm and the port/ offshore maintenance hub is determining the needed transit time and thus the in-field working time. The in-field working time is, in turn, influencing the required number of CTVs. The effect of the transit distance on the number of required CTVs is made clear by varying the transit distance from 0 to 100 nm while keeping all other settings the same.

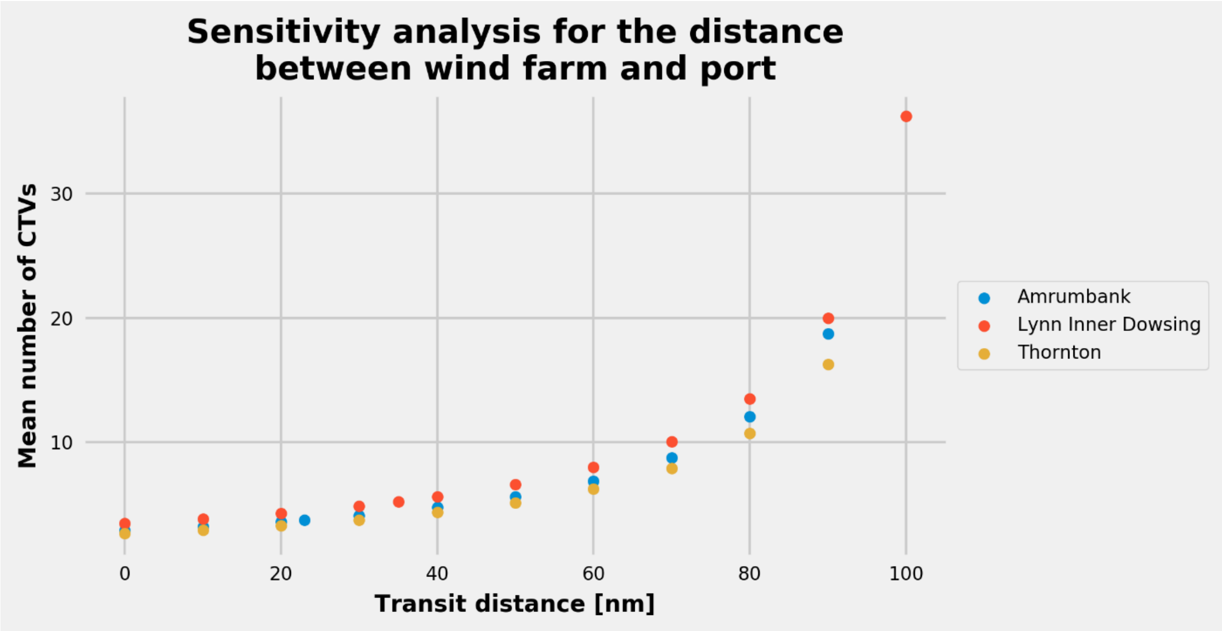

Figure 50: Sensitivity analysis for the transit distance for all three wind farms. Source: own composition.

The results of the analysis are shown in Figure 50. As can be seen, the analysis shows a similar trend for all three wind farms. The effect of the transit distance is more or less linear up to 30-40 nm. Thereafter, the effect is stronger and non-linear. This is due to the fact that at a certain point, the transit time becomes a significant part of the total working day. The transit time may be e.g. 100% of the working time when the transit distance is 100 nm (assuming that a CTV works 10 hours per day and has an average transit speed around 20 kts). In this case, the distance is too large to service the wind farm and the model output will be an infinite number of CTVs, as is the case for Amrumbank and Thornton for a transit distance of 100 nm. The effect of the transit distance on the required number of CTVs indicates the necessity to deploy SOVs and/ or make use of offshore maintenance hubs when the transit distance increases. Aforementioned in section 3.3, the maximum economic transit distance when using CTVs is around 30 to 35 nm. When using this model for wind farms located further from the port, the user should be aware of the fact that SOVs may be the primary mode of transport/ an offshore maintenance hub may be used.

8.7.3 Crew Transfer Vessel speed

It is believed that the SOG is of utmost importance for the efficiency of CTVs. The influence of the mean SOG during transits on the mean number of CTVs needed is tested, and the results are presented in this section.

The net effect of varying the SOG is evidently more significant for wind farms located further from the shore. However, when dividing the in-/ decrease by the nm transit, the effect is quite consistent, namely 0.15% - 0.18% in-/ decrease per kts per nm transit.

The number of required CTVs can be decreased slightly by increasing vessels' speed, and an additional effect is that technicians are less time waiting. However, the building costs and fuel costs are likely to increase (quadratic) when the vessel speed increases. It is expected that a slight SOG increase may be beneficial, since the daily technician costs are around three times the daily fuel costs (see appendix C.2). This gives some space to increase the vessel speed and lower the technicians' waiting time without extra costs. It is recommended to look into this case in more detail and to calculate if increasing the speed is economical/ the optimal speed.

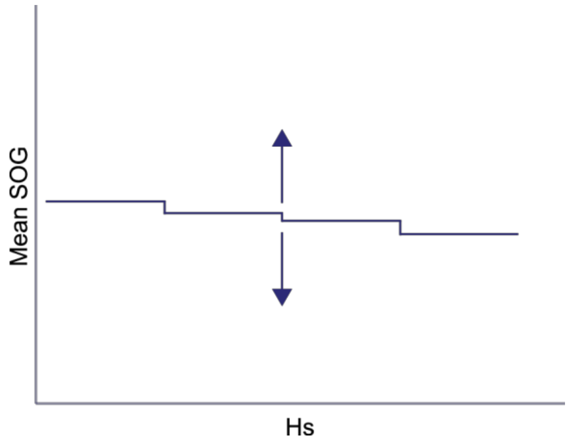

Figure 51: Changing mean SOG during transits for the sensitivity analysis. Source: own composition.

Table 25: Sensitivity analysis for the mean SOG during transits for Amrumbank. Source: own composition.

Amrumbank	**-5.0 kts**	**-2.5 kts**	**+0 kts**	**+2.5 kts**	**+5.0 kts**
Mean CTV demand	4.12	3.9	3.77	3.65	3.56
CTV demand in- / decrease	9%	3%	0%	-3%	-6%
CTV demand in- / decrease per nm transit	0.4%	0.1%	0.0%	-0.1%	-0.2%

Table 26: Sensitivity analysis for the mean SOG during transits for Lynn Inner Dowsing. Source: own composition.

Lynn Inner Dowsing	**-5.0 kts**	**-2.5 kts**	**+0 kts**	**+2.5 kts**	**+5.0 kts**
Mean CTV demand	6.13	5.58	5.23	4.97	4.78
CTV demand in- / decrease	17%	7%	0%	-5%	-9%
CTV demand in- / decrease per nm transit	0.5%	0.2%	0.0%	-0.1%	-0.2%

Table 27: Sensitivity analysis for the mean SOG during transits for Thornton. Source: own composition.

Thornton	**-5.0 kts**	**-2.5 kts**	**+0 kts**	**+2.5 kts**	**+5.0 kts**
Mean CTV demand	3.59	3.44	3.32	3.25	3.18
CTV demand in- / decrease	8%	4%	0%	-2%	-4%
CTV demand in- / decrease per nm transit	0.4%	0.2%	0.0%	-0.1%	-0.2%

8.7.4 Crew Transfer Operation demand

The effect of the CTO demand per turbine per year is tested by sliding the CTO demand distribution along the x-axis as is shown in Figure 52. The model is tested for sliding the distribution 10, 20, and 30 points to the left and right. The results are shown in Table 28, Table 29, and Table 30.

Not surprisingly, the sensitivity of the CTO demand on the mean CTV demand is nearly 1:1 as can be seen in the tables. So, if the CTO demand decreases by 10%, the mean CTV demand decreases with 10% as well.

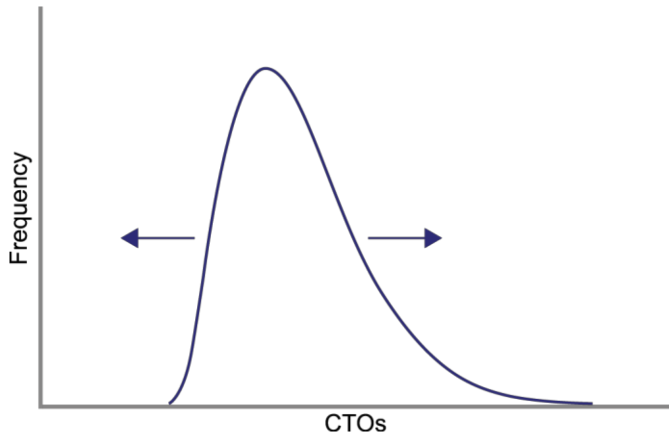

Figure 52: Changing CTO demand for the sensitivity analysis. Source: own composition.

Table 28: Sensitivity analysis for the CTO demand for Amrumbank. Source: own composition.

Amrumbank	**-30 CTOs**	**-20 CTOs**	**-10 CTOs**	**+ 0 CTOs**	**+10 CTOs**	**+20 CTOs**	**+30 CTOs**
Mean CTO demand / turbine / year	70.9	80.9	90.9	100.9	110.9	120.9	130.9
Mean CTV demand	2.64	3.01	3.38	3.77	4.13	4.53	4.88
CTO demand in- / decrease	-29.7%	-19.8%	-9.9%	0.0%	9.9%	19.8%	29.7%
CTV demand in- / decrease	-30.0%	-20.2%	-10.3%	0.0%	9.5%	20.2%	29.4%

Table 29: Sensitivity analysis for the CTO demand for Lynn Inner Dowsing. Source: own composition.

Lynn Inner Dowsing	**-30 CTOs**	**-20 CTOs**	**-10 CTOs**	**+ 0 CTOs**	**+10 CTOs**	**+20 CTOs**	**+30 CTOs**
Mean CTO demand / turbine / year	70.9	80.9	90.9	100.9	110.9	120.9	130.9
Mean CTV demand	3.67	4.19	4.71	5.23	5.75	6.26	6.76
CTO demand in- / decrease	-29.7%	-19.8%	-9.9%	0.0%	9.9%	19.8%	29.7%
CTV demand in- / decrease	-29.8%	-19.9%	-9.9%	0.0%	9.9%	19.7%	29.3%

Table 30: Sensitivity analysis for the CTO demand for Thornton. Source: own composition.

Thornton	**-30 CTOs**	**-20 CTOs**	**-10 CTOs**	**+ 0 CTOs**	**+10 CTOs**	**+20 CTOs**	**+30 CTOs**
Mean CTO demand / turbine / year	129.2	139.2	149.2	159.2	169.2	179.2	189.2
Mean CTV demand	2.7	2.9	3.1	3.32	3.54	3.74	3.96
CTO demand in- / decrease	-18.8%	-12.6%	-6.3%	0.0%	6.3%	12.6%	18.8%
CTV demand in- / decrease	-18.7%	-12.7%	-6.6%	0.0%	6.6%	12.7%	19.3%

This chapter presented the CTV Demand Model, which can be used to gain insights into the number of required CTVs to execute CTOs for a given wind farm. The CTO process is summarised, the model output and input is discussed, as well as the model assumptions. Moreover, the logic of the model is elaborated; based on key distribution figures, random selection of parameters and Monte Carlo is the CTO demand and CTO supply modelled and compared. In the second half of this chapter are the results of the CTV Demand Model presented. Furthermore, these results were validated and the sensitivity of input parameters was analysed. In the following chapter, potential applications are presented that are related to the CTV Demand Model.

9 Evaluation of Potential Applications

The CTV Demand Model is a tool that can be used for decision making and business development. This chapter discusses two potential applications that are related to the CTV Demand Model. The first application is an example of how the model can be used for the pricing strategy of a new hypothetical CTV with an extended weather window. The second application is a justification for investments in data analysis development (for market forecasting). All presented financial figures are for the year 2017.

9.1 Crew Transfer Operations in Mean Significant Wave Height up to 2.0 meter

At the moment, a Hs limit of 1.5 m is the industry standard for CTOs. As shown in section 8.7.1, quite some CTV capacity can be saved on a yearly basis when this limit can be stretched up to 2.0 m Hs. This case looks into the pricing of new CTVs that can transfer up to 2.0 m Hs, by analysing the potential operational cost savings. The potential higher pricing and cost savings provide Damen room for the development of a new CTV with an extended weather window.

The total yearly costs for the wind farm owner are calculated for both the 1.5 m Hs and 2.0 m Hs cases for Amrumbank, Lynn Inner Dowsing and Thornton. The difference in price is the amount that can be saved per year when using vessels that can transfer up to 2.0 m Hs instead of 1.5 m Hs. The yearly CTV costs for both cases are calculated with the following formula:

$$Yearly\ costs = mean\ number\ of\ CTVs * [yearly\ charter\ costs + yearly\ technician\ costs + (fuel\ costs\ per\ sailing\ day * number\ of\ sailing\ days)]$$

With:

Mean number of CTVs	=	*Model output*
Yearly charter costs	=	*€3,500 * 365 days = €1,277,500*
Yearly technician costs	=	*€7,000 * 365 days = €2,555,000*
Fuel costs per sailing day	=	*€2,350*
Number of sailing days	=	*365 * Access days (X%) * CTV availability (87%)*

The cost figures are explained in Appendix C.2, the mean number of CTVs for each case are shown in Table 31, the wind farm access days are given in Table 32 and the 87% CTV utilisation is adopted from section 7.2.2. Initially, the charter costs for a 1.5 m Hs vessel and a 2.0 m Hs vessel are kept the same, as are the fuel costs.

Table 31: Mean number of CTVs needed to service the wind farms according to the CTV Demand Model. Source: own composition.

	<= 1.5 m Hs	<= 2.0 m Hs
Amrumbank	3.77	3.08
Lynn Inner Dowsing	5.23	4.98
Thornton	3.32	2.93

Table 32: Access days: percentage of time for which the sea state is below 1.5 or 2.0 m Hs. Used data from MSG AIS Data Store, table is own composition.

	<= 1.5 m Hs	<= 2.0 m Hs
Amrumbank	69%	83%
Lynn Inner Dowsing	93%	98%
Thornton	79%	90%

9.1.1 Yearly cost savings

The total yearly costs of each case, rounded to thousands, are depicted in Table 33. Furthermore, the potential yearly cost savings, which is the difference between the 1.5 m and 2.0 m case, are shown. These savings are the most significant for Amrumbank, which is evident since the difference in access days and mean number of CTVs needed is the largest for Amrumbank as well. These cost savings can in theory be divided among all the stakeholders, such as the energy companies, wind farm owners, offshore service companies, shipbuilders and energy consumers. The potential cost savings means that Damen could price a 2.0 m Hs CTV higher than their current CTVs.

Table 33: Total yearly costs and potential savings. Source: own composition.

	<= 1.5 m Hs	<= 2.0 m Hs	Yearly savings
Amrumbank	€ 16,390,000. --	€ 13,712,000. --	€ 2,678,000. --
Lynn Inner Dowsing	€ 23,674,000. --	€ 22,728,000. --	€ 946,000. --
Thornton	€ 14,681,000. --	€ 13,197,000. --	€ 1,484,000. --

9.1.2 Increased charter prices

The potential yearly cost savings is calculated while keeping the charter price for both the 1.5 m Hs and 2.0 m Hs vessels at €3,500 per day. However, the charter price per vessel could increase – without changing the total yearly costs for the wind farm owner – if less vessels are required to conduct all the CTOs. Table 34 shows the daily charter price for the 2.0 m case per CTV per day for which the total yearly costs remain unchanged. The potential rise of charter prices is interesting for offshore service operators as they need less vessels to generate a higher income. This, in-turn, is interesting for Damen since the vessels may be priced higher if the daily charter rate is higher. As a rule of thumb, a vessel's day rate is 0.1% of its purchase price. By this rule of thumb, the 2.0 m Hs CTV may be priced at most €520,000 to €2,380,000 higher than a 1.5 m Hs CTV, depending on the wind farm location.

Table 34: Maximum daily charter price per CTV per day. Source: own composition.

	Total yearly costs	<= 1.5 m Hs	<= 2.0 m Hs	Difference
Amrumbank	€ 16,390,000. --	€ 3,500	€ 5,882	€ 2,382
Lynn Inner Dowsing	€ 23,674,000. --	€ 3,500	€ 4,020	€ 520
Thornton	€ 14,681,000. --	€ 3,500	€ 4,888	€ 1,388

This case shows that significant cost savings, and therefore potential revenues, can be achieved if a CTV can safely execute crew transfers up to 2.0 m. Based on this case, it is recommended to execute a more in-depth research, including a market research to verify customers' interest. Furthermore, it must be noticed that it is extremely difficult to prove that a vessel can safely transfer up to 2.0 m Hs, since e.g. the human factor plays a significant role in this. Convincing clients that it can be done safely and changing the industry standard may be a bigger hurdle than can be expected, which may consume some of the revenues.

It must be noticed that it is not very likely that in practice all CTVs will be replaced with 2.0 m Hs vessels. Perhaps only one or two 2.0 m Hs CTV are required per wind farm to increase the accessibility. Furthermore, the costs savings are presumably not divided equally among the stakeholders due to the market outlook and relative power of certain stakeholders. Nonetheless, this case indicates that there is potential market to develop 2.0 m Hs CTVs.

9.2 Opportunity Costs for Model Development

Aforementioned in the introduction, Damen keeps standardised vessels in stock, which significantly reduces delivery times. This concept gives Damen a great competitive advantage, but is not without risk since Damen must speculatively build vessels beforehand. This makes it extremely important for Damen to forecast the market and future vessel demand.

The decision to build vessels is mainly based on sales opportunities. These sales opportunities can be divided into three categories: enquiries (10% opportunity), serious interest to buy a vessel (50% opportunity), and contract negotiations (90% opportunity). The number and trends of these three opportunities form the basis to decide which vessels will be built to keep in stock. Of course, other factors such as occupancy rates of the yards, current stock levels, and market intelligence play a role in the decision-making process.

At the end of 2017, Damen has 7 FCS 2610 vessels in stock, of which the oldest is built in 2013. At least a few of these vessels are built too far up-front the market demand, as they are already in stock for quite some time. Keeping vessels in stock gives Damen a great competitive advantage, however, financing and maintaining the stock costs money. Therefore, it is desirable to keep just enough vessels in stock, and keep them in stock for only short times. Better forecasting the market may help Damen to achieve this.

This case looks into the potential direct costs savings that can be achieved when the stock time of a FCS 2610 can be reduced from two years to one year. This case is elaborated to show that quite some direct costs can be saved when the market can be forecasted better, with the aim to justify investments into AIS data analysis for market forecasting. This is of course a hypothetical case, as it cannot be guaranteed that investments into AIS data analysis will directly result in better stock management. However, it could definitely contribute to the decision-making process.

The finance and maintenance costs of one vessel are calculated with the Net Present Value (NPV) formula:

$$Net\ Present\ Value = \sum_{t=0}^{N} \frac{R_t}{(1+i)^t}$$

With:

N	=	*Total years*
t	=	*Year*
R_t	=	*Cash flow per year*
i	=	*Interest rate of 5% per year (=0.41% per month)*

For confidentiality reasons, a fictive cost price of €2 million is used as the initial investment needed to build the vessel, and the monthly costs for maintaining the stock is according to Damen around €1,100 per vessel. The cash flow of the last term is chosen in such a manner that the NPV is €0, meaning no profit/ loss is made if the vessel is sold for that price. The incoming cash flow of the last month, minus the initial investment is assumed to be the total stock costs for finance and maintenance.

Table 35 shows the results of the NPV calculation rounded to thousands. The cost price for keeping one CTV 12 months and 24 months in stock is respectively €112,000 and €232,000. This means that the extra costs of keeping a CTV 24 months instead of 12 months in stock is €120,000.

Table 35: Costs of stock for 1 CTV for 12 months and 24 months. Source: own composition.

	Initial investment	**Selling price (NPV = 0)**	**Costs for finance and maintenance of stock**
12 months	€2,000,000. --	€2,112,000. --	€112,000. --
24 months	€2,000,000. --	€2,232,000. --	€232,000. --

The potential direct cost savings of €120,000 by reducing the stock lead time from 24 months to 12 months may not seem extremely high at first sight. However, the price is quite significant when realising that Damen has a couple of hundred vessels in stock of which some are already in stock for quite a long time. The Damen FCS 2610 built in 2013, for example, already costs around €612,000 when using the above numbers and NPV calculation. This means that at some point the vessel must be sold with a loss. Investing in AIS data analysis to better forecast the market may help Damen to make better decisions concerning stock management, which may save a lot of money as is shown in this case. This case only focused on the direct costs, meaning that the opportunity costs may even be higher when also the indirect cost savings/ lost revenues are taken into account.

10 Conclusion & Discussion

In this final chapter is the conclusion and discussion presented. In the discussion is among others a recommendation for Damen and Made Smart Group presented.

10.1 Conclusion

The objective of this project is to determine if and how Big Data analysis can be used to model (future) demand for Crew Transfer Vessels being used for Crew Transfer Operations in the offshore wind industry. The conclusions of this project are presented in this section.

To start with the main conclusion: AIS data can be used to model vessel demand and gain insight into the market size. The crux of using AIS data is developing reliable and effective data mining methods to obtain the desired information and deal with the faults and limitations of the data.

10.1.1 Crew Transfer Vessel demand model

This project proves that it is possible to model CTV demand with the use of Big Data analysis. The developed method and model provides insights into the CTV demand of wind farms based on AIS- and sea state data. Furthermore, the impact of key variables can be researched. Despite this, the model does not yet provide an accurate picture of the actual CTV demand of individual wind farms, and wind farms other than the analysed three. This is due to the fact that the model is based on averages of multiple wind farms and that there are many more wind farm specific variables – e.g. the length of working days, year of operation, and monthly CTO distribution – correlated to the CTV demand that are not included in this model.

The accuracy of the model can be improved by adding: more wind farm specific variables; and data of more CTVs/ wind farms. Adding more wind farm specific input variables will make it possible to model the CTV demand more accurate for individual wind farms. However, it is not desirable to make the model more complex than is strictly necessary. Furthermore, the required information of wind farm specific variables may not be available. To get more accurate model results for the entire CTV market, more CTVs and wind farms should be analysed. This requires relatively little resources, as the method is already developed. In the discussion is an alternative approach suggested that may simplify the model.

10.1.2 Crew Transfer Vessel market size

The developed method and model are suitable for CTV market size and timing analysis. It adds value by providing a clearer picture of the total market outlook, despite that fact the total market size cannot be accurately modelled at the moment. The model can be used to quickly estimate the number of required CTVs for a new wind farm based on only the number of turbines, distance to port and sea state distribution. Furthermore, the effect of these parameters on the CTV demand can be verified.

The so far only research on this topic from the company 4C Offshore states that the market size is 1 CTV per 15.34 turbines (2016). The developed model, however, calculates the CTV demand based on two extra parameters in relation to 4C Offshore: distance to the port and sea state distribution. The developed model is therefore more suitable to gain insights into the CTV demand of specific wind farms/ regions. Furthermore, the CTV Demand Model models the demand per month to include the effect of seasonality. The results of this research are shown in Table 36, presented in the same format as the results of 4C Offshore to allow comparison. Due to the two extra input parameters, the results vary between the presented wind farms. The distance between port and wind farm is for example the shortest in Sheringham. Furthermore, the sea state is relatively calm in this wind farm as well. These parameters are reflected in the wind farm specific CTV demand for Sheringham.

Table 36: CTV market size expressed as variable of the number of turbines. Source: own composition.

Wind farm	Amrumbank	Lynn Inner Dowsing	Thornton	Meerwind Sud/ Ost	Sheringham
1 CTV per X turbines per year	14.3	15.3	10.3	15.7	18.8

10.1.3 Crew Transfer Vessel performance

Although the main focus of this project was not upon CTV performance and its operational profile, the project certainly did provide (new) insights into the operational profile of CTVs. First of all, the CTO is examined in detail to develop a method to identify CTOs based on AIS data, which contributed to the general knowledge on how CTOs are executed.

More detailed insights are obtained from the effect of the weather window and transit speed via a sensitivity analysis of the model. When the mean significant wave height limit for CTO can be increased from 1.5 m to 2.0 m, the number of required CTVs to fulfil the CTO demand decreases on average with 11% in the three analysed wind farms. This result in a potential cost saving around € 5.1 million on a yearly basis for these three wind farms alone. The effect of increasing the vessel speed is less significant. The CTV demand decreases on average only 4% and 6% when the speed is respectively increased with 2.5 kts and 5.0 kts. The number of required CTVs can be decreased slightly by increasing vessels' speed and technicians are less time waiting. However, the building costs and fuel costs will probably increase. This case should be worked out in more detail to calculate the net costs. These kinds of insights are extremely valuable for the development of new CTVs.

Another valuable insight obtained from this research is the significant difference in CTO demand between wind turbine types. The CTO demand of the turbines in Thornton are around 50% higher than those of Amrumbank and Lynn Inner Dowsing. This information may among others help developers to purchase less maintenance intensive turbines, and indirectly forces turbine manufacturers to improve the robustness of their products.

10.1.4 Other applications

The used method for this project can be used to model vessel demand for other applications as well. Furthermore, the developed method may be useful to improve existing models. The available AIS- and sea state data is used together with the wind farm and CTV specifications to derive key parameters and key performance indicators of the CTO process. These are then used to model the CTV demand (see Figure 53). The AIS data is primarily used to verify if certain conditions are met. This can be done for other applications as well, as long as the application of interest can be expressed in conditions that can be checked via AIS data. This project, however, cannot be copied one-to-one for other applications, since a thorough research is required to determine the outlook and influencing parameters of the application of interest.

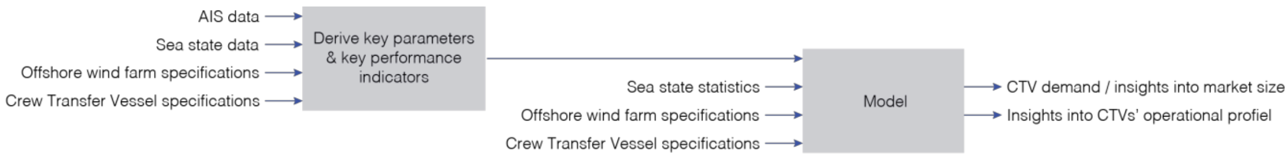

Figure 53: Used methodology. Source: own composition.

10.2 Discussion

The discussion of this research is elaborated in this section based on among others the importance and limitations of this research, recommendations for further research, and practical applications and recommendations for Damen and MSG.

As discussed in the introduction, Big Data analysis is an indispensable part of modern business environment and is among others used to gain market- and business insights that cannot be obtained via traditional market- and business intelligence. Damen is exploring the possible applications of Big Data analysis, and specifically AIS data analysis. This research is one of the first into the application of AIS data within Damen. The gained knowledge about using AIS data to forecast the CTV market size is very useful for the further introduction and future development of commercial AIS based data analysis.

Although this is a pioneering research, the company 4C Offshore (2016) conducted a research into the CTV market based on AIS data as well. They looked into vessels that where active in 26 wind farms to measure how many vessel days are required to service these wind farms. Their research resulted in a general figure of 1 CTV per 15.34 turbines to express the market size. This research, however, is more thoroughly. The AIS data is in combination with sea state data used to examine the CTO process in detail. This results in more in-depth knowledge about the CTV market and this research can be used to analyse the CTV market size more specifically. To name three examples: the CTV Demand Model can be used to gain insights into the differences between summer and winter; the usage of sea state data is valuable to research the differences between wind farms that are exposed to completely different conditions such as Lynn Inner Dowsing and Thornton; and this research can be used to analyse the CTO demand of different turbine types.

10.2.1 Limitations

The limitations of this research that may influence the results are discussed in this section. First, the AIS dataset contains some data gaps. Evidently, the vessel movements during the data gaps are not included in the analysis. This may result in the fact that some CTOs are missed, which in-turn, results in the fact that the measured CTO demand may be slightly too low. The effect of this is that the CTV demand may be slightly too low as well.

The amount of available data is limited to the year 2016, meaning that the results are a snapshot for this year. The analysed data should be extended to multiple years to gain insights into the effect of turbine age, turbine generations, differences between years etc. Furthermore, 2016 may have been an exceptional year that does not reflect the ‘normal’ market situation.

The wind farms analysed in this project are located relatively close the shore to ensure sufficient terrestrial AIS coverage, which is needed to obtain complete AIS datasets. Wind farms located further from the shore may require different O&M strategies than wind farms located closer to the shore. This may be reflected in e.g. the usage of other vessels to access the wind farms. The derived statistics from the wind farms close to the shore may therefore not be used for the wind farms located further from the shore.

This research only focused on CTVs, whereas other modes of transport such as Service Operations Vessels and helicopters may be used to execute the CTOs. This may mean that the CTO demand of some turbines may be higher than the demand measured based on the available AIS data.

Last, the long-term utilisation rate of CTVs is not investigated. The used rate of 87% is the utilisation during the contract period. Evidently, vessels are not under contract 100% of the time. Even in an ideal case this cannot be met due to vessel maintenance. To better forecast the market, the actual long term CTV utilisation rate should be known.

10.2.2 Recommendations for further research

During the execution of this project, many interesting topics for further research arose. These topics are briefly discussed in the following part. First of all, it is recommended to examine other possible AIS data applications for shipping management purposes. AIS data contains a lot of information that can be used (in combination with other data sources) to determine the market size, optimise routes, improve offshore operations, investigate vessel usage, etc. These kinds of applications may help Damen (and other companies) to optimise their performance, design better vessels, predict maintenance, etc. Therefore, an exploratory research into the possible applications is recommended to start the usage of AIS data analysis.

A more specific interesting topic for further research is the influence of turbine type, age and make on the yearly CTO demand. From the literature study, it is clear that there is a lack of practical based knowledge on this topic. Furthermore, the significant difference between the number of CTOs executed per turbine – as shown in Figure 31 in section 7.1.1 – indicates that there is a relation between turbine type, age and make and the CTO demand. This study would be interesting for the entire offshore wind industry, since CTO demand is directly correlated to the required number of CTVs and maintenance costs.

The following two recommendations for further research are about how the data is used. First, the turbine locations required for this project are obtained from the AIS data by making use of the DBSCAN algorithm. This algorithm, as used for this project, required quite some manual testing and worked only for two of the three wind farms. Detecting frequently visit locations from the AIS data may be beneficial for a dozen of other applications as well. Locations may be very specific such as wind turbines, platforms and locks, but could perhaps be regions such as ports and canals as well. An interesting field of further study is the development of a solid working method to automatically derive this information from AIS data. Such an algorithm would speed up the analysis performed for this project significantly.

Second, in this project are two data sources used to identify CTOs: AIS data and turbine locations. It may be possible to identify CTOs based on only the AIS data by applying machine learning techniques. This would make it much easier to (real time) analyse a large number of CTVs and wind farms. A CTO may for example be identified based on CTVs' speed, location and heading over time. Automatically identifying manoeuvres from AIS data may be applicable for other operations as well, such as tugs, pilot vessels, bunker vessels and ferries. It is recommended to look into this, especially for its potential to automatically analyse large number of vessels and thereby better analysing entire markets (real time).

10.2.3 Practical applications & recommendations

In this section are the practical applications and recommendations of this project presented. First of all, Damen is recommended to start a full time AIS project team that is part of a structured plan to utilise the value of AIS data. All the possible applications of AIS data and their commercial value is difficult to know/

quantify beforehand. Therefore, it may be difficult to get the required resources to start developing AIS based information tools. This is unfortunate, because AIS data (in combination with sea state data) is a rich source of information for a wide range of applications. The data can among others be used to developed detailed operational profiles, market forecasting, route optimisation, learning platform for e.g. pilots, scanning clients sailing within the yard's range, warranty claims, trail records, etc.

In an optimal case, a small project team would work fulltime to explore these applications and to develop methods to obtain the desired information. The key to successfully implement this into an organisation is communication. The people working in all the different departments of an organisation should be informed about the explored and developed applications. Conversely, they should feed the project team with requests for information that would be beneficial for them. To get the conversation started, it is recommended to develop a few solid business cases to roll-out AIS based data analysis.

The second recommendation is for both Damen and MSG and is specifically for the CTV demand model. With hindsight, it is recommended to explore a different method to analyse the market size of CTVs. The developed model is quite detailed as it is zoomed in on the CTO level. Based on this research it can be concluded that this is not needed when analysing the CTV demand of the entire market.

An alternative approach is to view a wind farm as a black box and derive key figures by keeping track of all the vessels entering and leaving the wind farm, without analysing what they do within the wind farm. This will result in a less complex model, which makes it possible to easily analyse a large number of CTVs/ wind farms. Analysing more vessels and wind farms will result in better key figures that reflect the entire market. Furthermore, it may be possible to apply this model real time as it is relatively simple.

This alternative approach is quite similar to the approach used by 4C Offshore (2016). 4C Offshore only considered the number of turbines as a factor determining the CTV demand. The develop method for this project can be used to extend the number of influencing factors by adding e.g. the distance between port and wind farm, and the sea state distribution.

The above proposed approach is only suitable when the objective is to analyse the CTV market as a whole. Information about the CTO demand of specific wind farms cannot be obtained via this approach, neither can this approach be used to accurately model the CTV demand of specific individual wind farms. If the latter is the objective, it is recommended to extend the for this research developed with more wind farm specific input variables.

The third recommendation is to look into the 2.0 m Hs transfer case in more detail. As is indicated in the case in section 9.1, serious cost savings could be accomplished if CTVs could safely execute CTOs in Hs up to 2.0 m. Therefore, it is recommended to perform a study into the technical- and financial feasibility of these vessels. Similar to the 2.0 m Hs transfer case, it is recommended to look into the effect of increasing the design speed of CTVs. The CTV Demand Model can be used to determine the theoretical optimal design speed. These studies would not only be interesting for Damen, but also for offshore service operators and wind farm owners.

Fourth, MSG is recommended to use this project to develop two business cases to sell their information services to wind farm owners, turbine manufacturers and offshore service operators. First, the for this project developed method can be used to verify which turbines require the least CTOs over time. Turbines that require less CTOs than its peer group are likely to require less maintenance, and are therefore likely to be more economical. This research proved for example that the turbines in Thornton required 50% more CTOs than the turbines in Amrumbank and Lynn Inner Dowsing, indicating that the OPEX of Thornton is higher. This information is valuable for wind farm owners for the development of new wind farms and turbine manufacturers to validate the quality of their products.

Secondly, this research showed that human factors can significantly influence the CTV demand. AIS data can be used to monitor some of these human factors, such as the working time per day. Wind farm operators can e.g. use this information to assign contracts to operators that work more hours per day. This information may also be beneficial for offshore service operators, as they can use the key figures as a benchmark to monitor and improve their operations.

This concluding chapter elaborated on the conclusion and discussion of this research. This pioneering research proved that AIS data can be used to model vessel demand, and is a valuable source of information for the maritime industry. It is therefore strongly recommended to allocate financial and human resources to AIS data analysis to utilise its value.

References

4C Offshore, 2016. *Wind Farm Service Vessels– An Analysis of Supply and Demand,* s.l.: s.n.

4C Offshore, 2017a. *Global Offshore Map.* [Online] Available at: http://www.4coffshore.com/offshorewind/ [Accessed 1 May 2017].

4C Offshore, 2017b. *4C Offshore: wind farm service vessel database,* Lowestoft: 4C Offshore.

4C Offshore, 2017c. *4C Offshore: offshore wind farms database,* Lowestoft: 4C Offshore.

Aarseather, K. & Moan, T., 2009. Estimating Navigation Patterns from AIS. *The Journal of Navigation,* 62(4), pp. 587-607.

Besijn, M., 2017. *Damen Marine Services: Charter contracts* [Interview] (20 April 2017).

Bloomberg, 2016. *H2 2016 LCOE: Giant fall in generating costs from offshore wind.* [Online] Available at: https://about.newenergyfinance.com/about/blog/h2-2016-lcoe-giant-fall-generating-costs-offshore-wind/ [Accessed 4 April 2017].

Bloomberg, 2017. *Gigantic Wind Turbines Signal Era of Subsidy-Free Green Power.* [Online] Available at: https://www.bloomberg.com/news/articles/2017-04-20/gigantic-wind-turbines-signal-era-of-subsidy-free-green-power [Accessed 26 April 2017].

Bos, J. & Houben, M., 2013. *Optimising Operator Performance by Reducing Seasickness with an Artificial 3D Earth-fixed Visual Reference.* Brest, s.n.

Breton, S. & Moe, G., 2009. Status, plans and technologies for offshore wind turbines. *Renewable Energy,* 34(3), pp. 646-654.

Britisch Petroleum, 2017. *Energy Outlook downloads and archive.* [Online] Available at: http://www.bp.com/en/global/corporate/energy-economics/energy-outlook/energy-outlook-downloads.html [Accessed 30 March 2017].

Bunker Index, 2017. *North & Atlantic Europe: Regional Prices.* [Online] Available at: http://www.bunkerindex.com/prices/neurope.php [Accessed 2 May 2017].

Carbon Trust, 2017. *Crew Transfer Vessel (CTV) Performance Plot (P-Plot) Development,* London: The Carbon Trust.

Carroll, J. et al., 2017. Availability, operation and maintenance costs of offshore wind turbines with different drive train configurations. *Wind Energy,* 20(2), pp. 361-378.

Carroll, J., McDonald, A. & McMillan, D., 2015. Reliability Comparison of Wind Turbines With DFIG and PMG Drive Trains. *IEEE Transactions on Energy Conversion,* 30(2), pp. 663-670.

Carroll, J., McDonald, A. & McMillan, D., 2016. Failure rate, repair time and unscheduled O&M cost analysis of offshore wind turbines. *Wind Energy,* 19(6), pp. 1107-1119.

Colwell, J., 2005. Modeling Ship Motion Effects on Human Performance for Real Time Simulation. *Naval Engineers Journal,* 117(1), pp. 77-90.

Costello, T. & Prohaska, B., 2013. Trends and Strategies. *IT Professional,* 15(1), pp. 64-64.

C-Power, 2017. *C-Power Jackets.* [Online] Available at: http://www.c-power.be/index.php/technology/jackets [Accessed 12 October 2017].

Crabtree, C., Zappala, D. & Hogg, S., 2015. Wind energy: UK experiences and offshore operational challenges. *Proceedings of the Institution of Mechanical Engineers Part A: Journal of Power and Energy,* 229(7), p. 727–746.

CWind, 2017. *CWind grows fleeet of crew tranfer vessels.* [Online] Available at: http://cwind247.com/cwind-grows-fleet-of-crew-transfer-vessels/ [Accessed 3 July 2017].

Dalgic, Y. et al., 2015b. Advanced logistics planning for offshore wind farm operation and maintenance activities. *Ocean Engineering,* Volume 101, pp. 211-226.

Dalgic, Y. et al., 2015c. Cost benefit analysis of mothership concept and investigation of. *Energy Procedia,* Volume 80, pp. 63-71.

Dalgic, Y., Lazakis, I. & Turan, O., 2015a. Investigation of Optimum Crew Transfer Vessel Fleet for Offshore Wind Farm Maintenance Operations. *Wind Engineering,* 39(1), pp. 31-52.

Damen, 2014. *Damen Fast Crew Supplier 2610.* [Online] Available at: http://products.damen.com/-/media/Products/Images/Clusters-groups/High-Speed-Crafts/Fast-Crew-Supplier/FCS-2610/Documents/Damen_Fast_Crew_Supplier_2610_Twin_Axe.pdf [Accessed 19 July 2017].

Damen, 2017. *Fast Crew Supplier 2610.* [Online] Available at: http://products.damen.com/en/ranges/fast-crew-supplier/fcs-2610 [Accessed 3 July 2017].

Dinwoodie, I. et al., 2015. Reference Cases for Verification of Operation and Maintenance Simulation Models for Offshore Wind Farms. *Wind Engineering,* 39(1), pp. 1-14.

ECN, 2016. *Reference O&M Concepts for Near and Far Offshore Wind Farms,* Petten: ECN.

Ecofys, 2014. *Subsidies and costs of EU energy,* s.l.: s.n.

Ester, M., Kriegel, H.-P., Sander, J. & Xu, X., 1996. A density-based algorithm for discovering clusters in large spatial databases with noise. *Kdd,* 96(34), pp. 226-231.

ESVAGT, 2017. *Our Fleet.* [Online] Available at: http://www.esvagt.com/fleet/fleet-overview/ [Accessed 3 Juli 2017].

European Commission, 2017c. *Assessing the European clean energy finance landscape, with implications for improved macro-energy modelling,* Brussels: s.n.

EY, 2015. *Osshore wind in Europe: Walking the tightrope to success,* s.l.: Ernst & Young (EY).

Faulstich, S., Hahn, B. & Tavner, P., 2011. Wind turbine downtime and its importance for offshore deployment. *Wind Energy,* 14(3), pp. 327-337.

GWEC, 2016. *Global Wind Report: Annual market update 2015,* Brussels: Global Wind Energy Council (GWEC).

Harati-Mokhtari, A., Wall, A., Brooks, P. & Wang, J., 2007. Automatic Identification System (AIS): Data Reliability and Human Error Implications. *The Journal of Navigation,* 60(3), pp. 373-389.

IMO, 2017a. *AIS transponders.* [Online] Available at: http://www.imo.org/en/OurWork/Safety/Navigation/Pages/AIS.aspx [Accessed 4 April 2017].

IMO, 2017b. *Passenger ships.* [Online] Available at: http://www.imo.org/en/OurWork/Safety/Regulations/Pages/PassengerShips.aspx [Accessed 13 March 2017].

Irawan, C. et al., 2017. Optimisation of maintenance routing and scheduling for offshore wind farms. *European Journal of Operational Research,* 256(1), pp. 76-89.

IRENA, 2012. *Renewable Energy Technologies: Cost Analysis Series. Volume 1: Power Sector, Issue 5/5,* Bonn: International Renewable Energy Agency (IRENA).

IRENA, 2017. *Renewable Capacity Statistics 2017,* Abu Dhabi: International Renewable Energy Agency (IRENA).

LaValle, S. et al., 2011. Big Data, Analytics and the Path From Insights to Value. *MIT Sloan Management Review,* 52(2), pp. 21-31.

Lugmayr, A., Stockleben, B., Scheib, C. & Mailaparampil, M., 2017. Cognitive big data: survey and review on big data research and its implications. What is really "new" in. *Journal of Knowledge Management,* 21(1), pp. 197-212.

Made Smart Group, 2017. *The World's Largets AIS Data Store By Made Smart Group.* [Online] Available at: http://www.madesmart.nl/worlds-largest-ais-data-store/ [Accessed 14 March 2017].

McAfee, D. & Brynjolfsson, E., 2012. Big Data: The Management Revolution. *Harvard Business Review,* 90(10), pp. 61-68.

Offshore Wind Industry, 2017. *Automated drone technology in offshore turbine inspections.* [Online] Available at: http://www.offshorewindindustry.com/news/automated-drone-technology-offshore-turbine [Accessed 16 June 2017].

OffshoreWIND.biz, 2016. *Oil & Gas Giant to Build Dutch Borssele III & IV Offshore Wind Farms.* [Online] Available at: http://www.offshorewind.biz/2016/12/12/oil-gas-giant-to-build-dutch-borssele-iii-iv-offshore-wind-farms/ [Accessed 4 April 2017].

OffshoreWind.biz, 2017a. *Artificial Intelligence Meets Offshore Energy.* [Online] Available at: http://www.offshorewind.biz/2017/11/09/artificial-intelligence-meets-offshore-energy/?utm_source=emark&utm_medium=email&utm_campaign=daily-update-offshore-wind-2017-11-10&uid=68123 [Accessed 9 November 2017].

OffshoreWIND.biz, 2017b. *Dutch MPs Call For Extension of 2023 Offshore Wind Capacity Target.* [Online] Available at: http://www.offshorewind.biz/2017/02/08/dutch-mps-call-for-extension-of-2023-offshore-wind-capacity-target/ [Accessed 26 April 2017].

Powers, D., 2011. Evaluation: From Precision, Recall and F-Factor to ROC, Informedness, Markedness & Correlation. *Journal of Machine Learning Technologies,* 2(1), pp. 37-63.

Shafiee, M., 2015a. Maintenance logistics organization for offshore wind energy: Current progress and future perspectives. *Renewable Energy,* 77(4), pp. 182-193.

Shafiee, M., 2015b. A fuzzy analytic network process model to mitigate the risk associated with offshore wind farms. *Expert Systems with Applications ,* 42(4), p. 2143–2152.

Shafiee, M., Brennan, F. & Espinosa, I., 2016. A parametric whole life cost model for offshore wind farms. *The International Journal of Life Cycle Assessment,* 21(7), pp. 961-975.

Shearer, C., 2000. The CRISP-DM Model: The New Blueprint for Data Mining. *Journal of Data Warehousing,* 5(4), pp. 13-22.

Sif Group, 2017. *Wind foundations.* [Online] Available at: https://sif-group.com/en/wind/foundations [Accessed 12 October 2017].

Smart, G. et al., 2016. *IEA Wind Task 26 - Offshore Wind Farm Baseline Documentation,* s.l.: IEA Wind.

SPARTA, 2017. *Portfolio Review 2016,* London: Systems Performance, Availability and Reliability Trend Analysis.

Sperstad, I. et al., 2016. Investigating Key Decision Problems to Optimize the Operation and Maintenance Strategy of Offshore Wind Farms. *Energy Procedia,* Volume 94, pp. 261-268.

Tavner, P., 2012. *Offshore wind turbines: Reliability, availability and maintenance.* London: The Institution of Engineering and Technology.

Ueckerdt, F., hirth, L., Luderer, G. & Edenhofer, O., 2013. System LCOE: What are the costs of variable renewables?. *Energy,* Volume 63, pp. 61-75.

Vahn, G., 2014. Business analytics in the age of Big Data. *Business Strategy Review,* 25(3), pp. 8-9.

Vera-Baquero, A., Palacios, R., Stantchev, V. & Molloy, O., 2015. Leveraging big-data for business process analytics. *The learning Organization,* 22(4), pp. 215-228.

WindEurope, 2017a. *Wind in power: 2016 European statistics,* Brussels: s.n.

WindEurope, 2017b. *The European offshore wind industry: Key trends and statistics 2016,* Brussels: s.n.

Wiser, R. et al., 2016. *Forecasting Wind Energy Costs and Cost Drivers: The Views of the World's Leading Experts,* s.l.: s.n.

Wu, L. et al., 2017. Mapping Global Shipping Density form AIS Data. *The Journal of Navigation,* 70(1), pp. 67-81.

Yang, W. et al., 2015. Wind turbine condition monitoring: technical and commercial challenges. *Wind Energy,* 17(5), pp. 673-693.

Appendix A: Offshore Wind Background Information

This appendix contains additional background information about offshore wind. The most relevant information for this project is already presented in the introduction.

A.1 Offshore Wind Market

The European offshore wind market is by far the biggest market in the world. In 2015 and 2016, the European market accounted for respectively more than 94% and 88% of the total worldwide capacity (11,637 MW in 2015 and 14,081 MW in 2016) (GWEC, 2016; IRENA, 2017). Asia is the second market, with China (1,480 MW), Japan (60 MW) and Korea (41 MW). Newcomers are the US that finished its first 27 MW offshore wind farm in 2016, and also India is likely to announce its first tender in 2018 (GWEC, 2016; IRENA, 2017). According to EY (2015), the cumulated worldwide investment in offshore wind will be approximately €690 billion by 2040. This could be a huge market for European players who invested in know-how.

At the end of 2016, the European offshore wind market had a total installed capacity of 12.6 GW spread over 81 wind farms in 10 countries. This is just a humble beginning, as WindEurope (2017b) reports that this capacity will be extended to a total of 24.6 GW by 2020. Moreover, they state that a total of 65.5 GW of projects are currently in the pipeline. This is a significant market when realizing that a total investment of €18.2 billion was required to install 4.9 GW in 2016 (WindEurope, 2017b).

Europe is the forerunner of the offshore wind market, which has been growing rapidly over the past years in the light of climate change and the needed energy transition towards renewables. The outlook for the coming years is positive, as Europe and other markets are investing a lot. This means that the market has potential for Damen to sell CTVs. 4C Offshore (2016) – a consultancy and market research firm – roughly estimated that the demand for CTVs for operation and maintenance is approximately 1 vessel per year per 15 turbines. Although this number might be inaccurate (for future offshore wind farms), it indicates the significance of the CTV market. This number of 4C Offshore can be verified based on AIS data, which is part of this research. This, together with other and more precise market insights may help Damen to better serve the offshore wind market.

A.2 Competitiveness of Offshore Wind Energy

The Levelised Cost of Energy (LCOE) is a measure that can be used to compare the cost price of power generation of different power sources. It gives a cost price per MWh based on the total lifetime costs and generated energy, and can be calculated with the following formula (Ueckerdt, et al., 2013):

$$LCOE = \frac{Net\ Present\ Value\ (CAPEX + OPEX)}{Net\ Present\ Value\ (Generated\ Energy)} = \frac{I_0 + \sum_{t=1}^{n} \frac{CAPEX_t + OPEX_t}{(1+r)^t}}{\sum_{t=1}^{n} \frac{E_t}{(1+r)^t}}$$

With:

I_0	=	*Investment costs in year 0*
$CAPEX_t$	=	*Capital Expenditures in year t*
$OPEX_t$	=	*Operational Expenditures in year t*
E_t	=	*Generated power in year t*
r	=	*Discount rate*
n	=	*Economic lifetime*
t	=	*Year of economic lifetime (1, 2, ..., n)*

Evidently, the competitive position of a power generating technique becomes better when the LCOE decreases. The blue bars in Figure 54 represent the LCOE of different power sources. It must be noticed that the values of the LCOE of some sources might have shifted slightly to the left due to technological and/ or market developments. Nonetheless, it can be seen that offshore wind energy is not (yet) competitive, explaining the current necessity of subsidies (OffshoreWIND.biz, 2016). However, the LCOE of offshore wind is falling due to competition and (technological) developments as Bloomberg (2016) points out.

The current LCOE of new offshore wind farms is more likely to lie within the range of the orange bar in Figure 54. In December 2016, a consortium of Shell, Van Oord, Eneco and DGE won the tender for the Borssele III and IV wind farms in the Netherlands with a bid of 54.5 €/MWh (OffshoreWIND.biz, 2017b). Moreover, in Germany DONG Energy will build the first subsidy-free wind farm, indicating an even further reduction of the LCOE. This reduction is to the utmost extent caused by increasing turbine capacities (Bloomberg, 2017). However, also on the 'top side' of the LCOE formula are reductions needed to realise subsidy free offshore wind power, putting pressure on among others O&M activities including CTV usage.

Off course, it is not yet known if Borssele III and IV and the German subsidy-free wind farm will be profitable, but the low prices certainly set a new benchmark for competition and the future. Although a big step forward is made, a further reduction of the LCOE of offshore wind is evidently needed to make it a competitive source of energy and to abate the necessity of subsidies for all wind farm.

A.3 Wind Farm Revenue

The daily revenue of a wind turbine can be calculated with the following simplified formula:

$$\begin{aligned} Daily\ revenue\ &= Turbine\ Capacity * 24\ hours * Income\ /\ MWh \\ &* power\ output\ as\ percentage\ of\ turbine\ capacity \end{aligned}$$

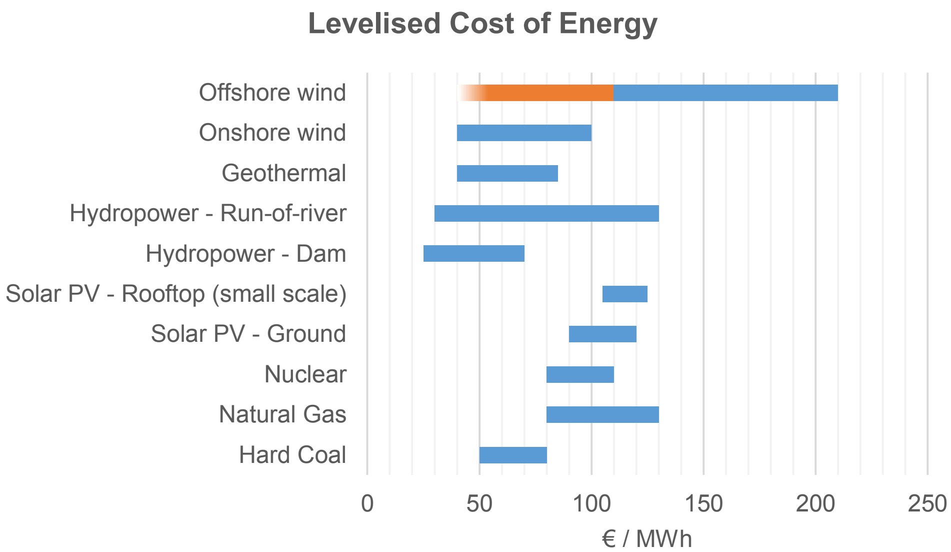

Figure 54: Levelised Cost of Energy. Onshore and offshore wind data from European Commission (2017c), rest from Ecofys (2014), figure own composition.

The daily revenue per wind turbine capacity is shown in Figure 55 (a). The used income per MWh in this graph is €54.5, equal to the very low LCOE of the Borssele III and IV wind farms (OffshoreWIND.biz, 2017b). For example, the daily revenue of a modern wind farm with 100 * 8 MW turbines with an average power output of 80% over the course of the day is around €0.84 million.

Figure 55 (a) is not completely representative for all wind farms, since older wind farms are mostly heavily subsidised by governments (OffshoreWIND.biz, 2016). In these cases, the government generally guarantees a fixed income per MWh independent from market prices. These schemes are/ were needed to develop the industry. This means that an old 100 * 4 MW wind farm may e.g. receive €100 / MWh, resulting in a daily revenue of €0.77 million. This is quite high when compared to the €0.84 million of a modern wind farm. The effect of the income per MWh is illustrated in Figure 55 (b).

A.4 Crew Transfer Operations & Crew Transfer Vessels

20% to 30% of the LCOE of offshore wind is related to Operation and Maintenance (O&M), of which vessel costs account for approximately 50% (Dalgic, et al., 2015a; Shafiee, 2015a; Carroll, et al., 2016). According to Dalgic et al. (2015a), more than 40% of the vessels used in the offshore wind industry are CTVs. When assuming that 40% of the vessels equals 40% of the vessel costs, CTV costs account for approximately 4% to 6% of the LCOE of offshore wind. An enormous cost reduction of 25% of the CTV costs would only result in a 1% to 1.25% reduction of the LCOE. At first sight this may seem little, but this is around 0.50 to 1.00 €/MWh.

Apart from cost reduction, there is another reason to focus on CTVs. CTVs are a tool to access offshore wind turbines for O&M purposes, and therefore an important link in the value chain of offshore wind. According to Dalgic et al. (2015a) the lost revenue of a 5 MW turbine is 10,000 to 19,000 GBP per downtime day. In practice, Dalgic's et al. lower limit is more realistic than their upper limit (see section A.3). Furthermore, the lost revenue is strongly correlated to the energy price, turbine capacity and wind speed. Nonetheless, minimising downtime has a direct major influence on the revenue and thus on the LCOE. Therefore, Increasing CTVs' performance, efficiency and usage to better access the wind turbines may be an effective way to contribute to a reduction of the LCOE of offshore wind.

As mentioned, Damen is a major supplier of CTVs that are required for Crew Transfer Operations during the whole lifetime of offshore wind farms. Therefore, Damen wants to learn more about the operational profile of CTVs being used for CTOs in the offshore wind industry. This may help Damen to improve the functional specifications of their vessels, to better serve clients, to create competitive advantage and to develop new business models.

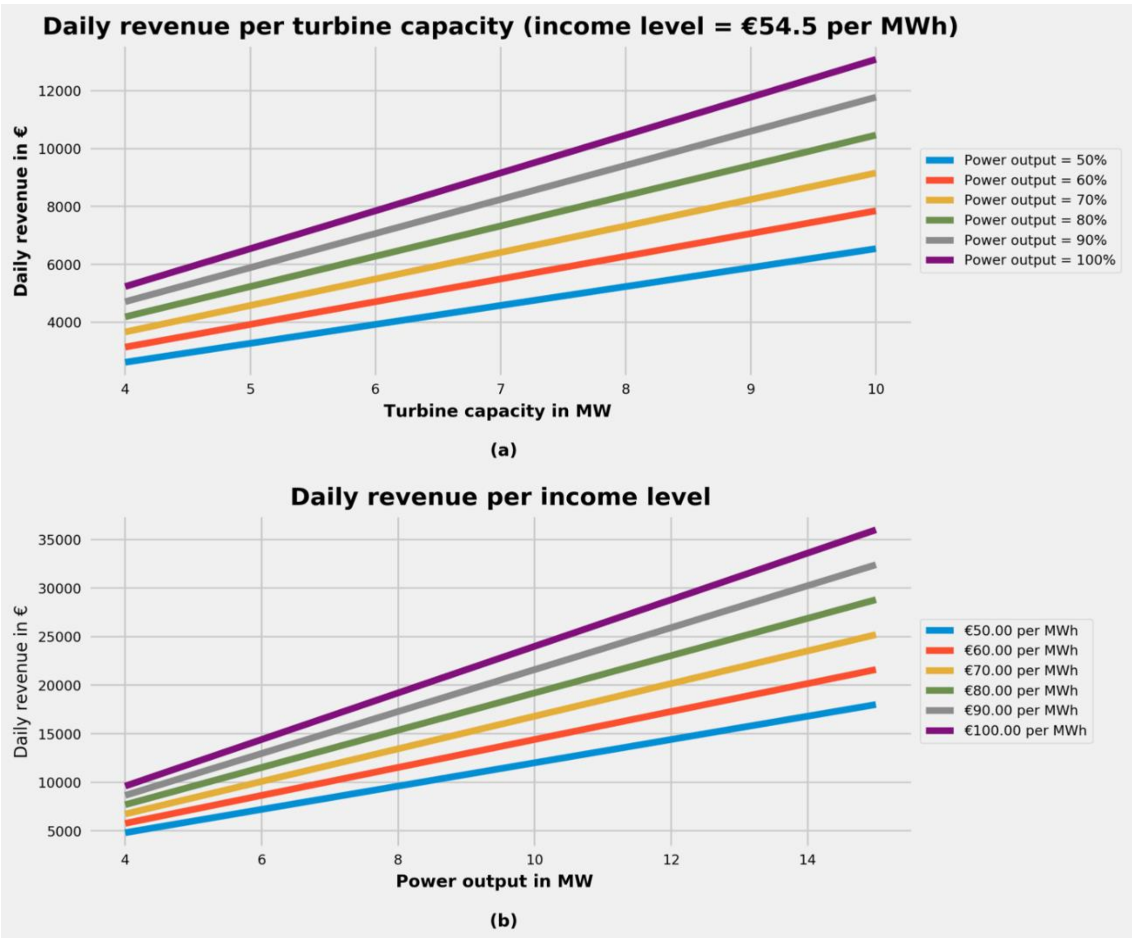

Figure 55: Daily revenue per turbine capacity (a) and per level of income per MWh (b). Source: own composition.

Appendix B: Wind Farm Specifications

B.1 Wind Farm Specifications

Table 37: Offshore wind farm specification. Data from 4C offshore (2017c). Distance to port is measured in MSG Plotter.

Wind farm	Country	Distance to shore	Maintenance port	Distance to port	GPS Centre	Total Power	# turbines	First Power	Make
Amrumbank West	Germany	44 km	Helgoland	± 42.5 km	54.523°, 7.705°	302 MW	80	22 Oct. 2015	Siemens SWT-3.6-120
Thornton Bank Phase I	Belgium	27 km	Oostende	± 37.0 km	51.544°, 2.938°	30 MW	6	10 May 2009	Senvion 5M
Thornton Bank Phase II	Belgium	28 km	Oostende	± 37.0 km	51.556°, 2.969°	184.5 MW	30	31 Jan. 2013	Senvion 6.2M126
Thornton Bank Phase III	Belgium	28 km	Oostende	± 37.0 km	51.540°, 2.922°	110.7 MW	18	18 Sep. 2013	Senvion 6.2M126
Lynn	United Kingdom	6 km	Grimsby	± 64.7 km	53.136°, 0.458°	97.2 MW	27	March 2009	Siemens SWT-3.6-107
Inner Dowsing	United Kingdom	6 km	Grimsby	± 64.7 km	53.191°, 0.446°	97.2 MW	27	March 2009	Siemens SWT-3.6-107
Lincs	United Kingdom	9 km	Grimsby	± 64.7 km	53.191°, 0.491°	270 MW	75	27 Sep. 2013	Siemens SWT-3.6-120

Figure 56 illustrates the used method for measuring the sailing distance from wind farm to port for the Amrumbank. In MSG Plotter one can measure the distance between two points. The black track of a CTV is used to measure the sailing distance between Amrumbank and Helgoland. The sum of the lengths of the red dotted lines in Figure 56 is an approximation of the total sailing distance. The same method is used for measuring the sailing distances for the other wind farms.

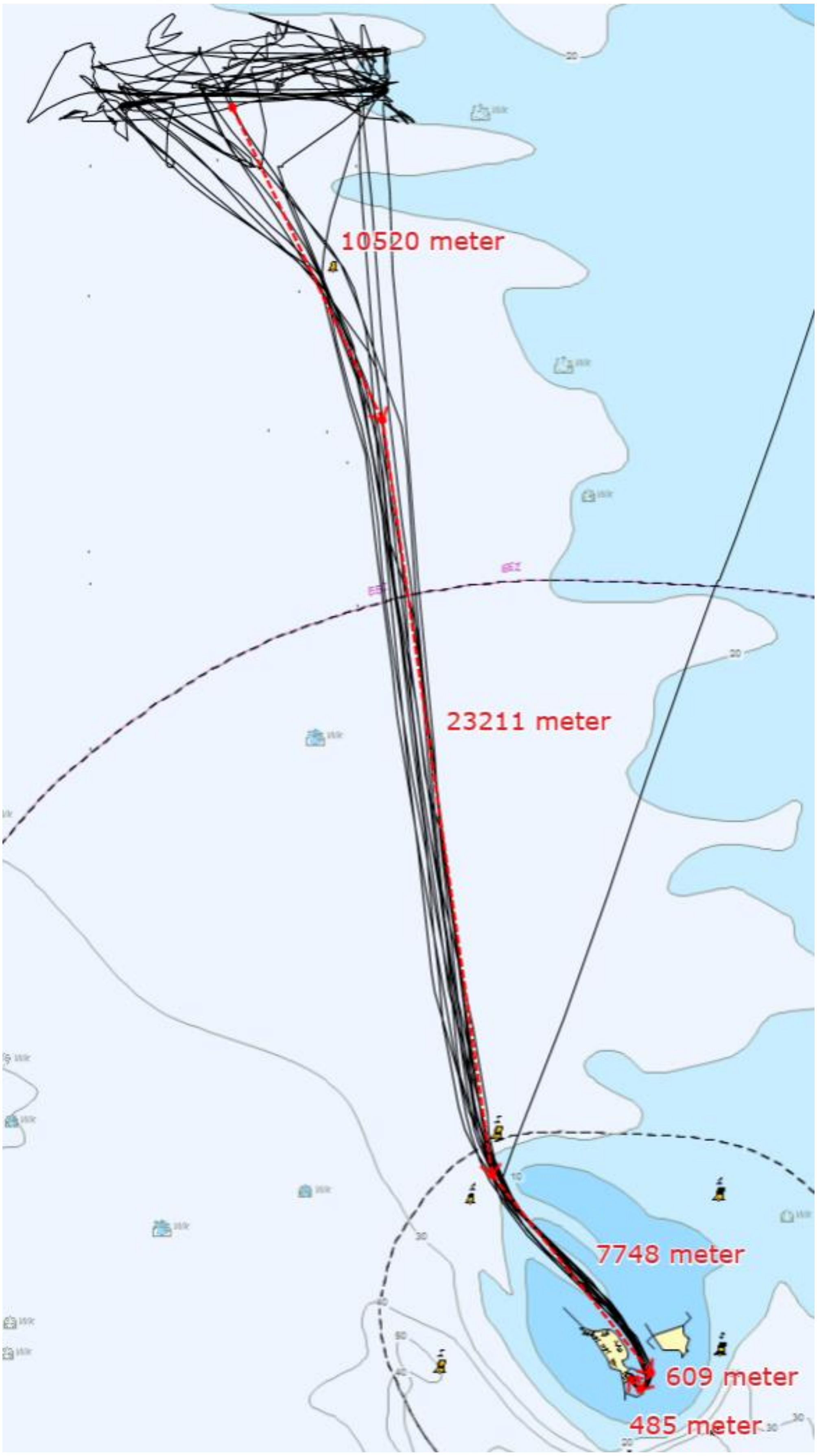

Figure 56: Distance between Amrumbank wind farm and Helgoland maintenance port. Figure composed in MSG Plotter.

B.2 Sea State Distributions

The underneath sea state distributions give an idea about the conditions at the wind farms. As can be seen, Lynn Inner Dowsing is located in a calm area. In the CTV Demand Model, distributions per month are used to incorporate the effect of seasonality.

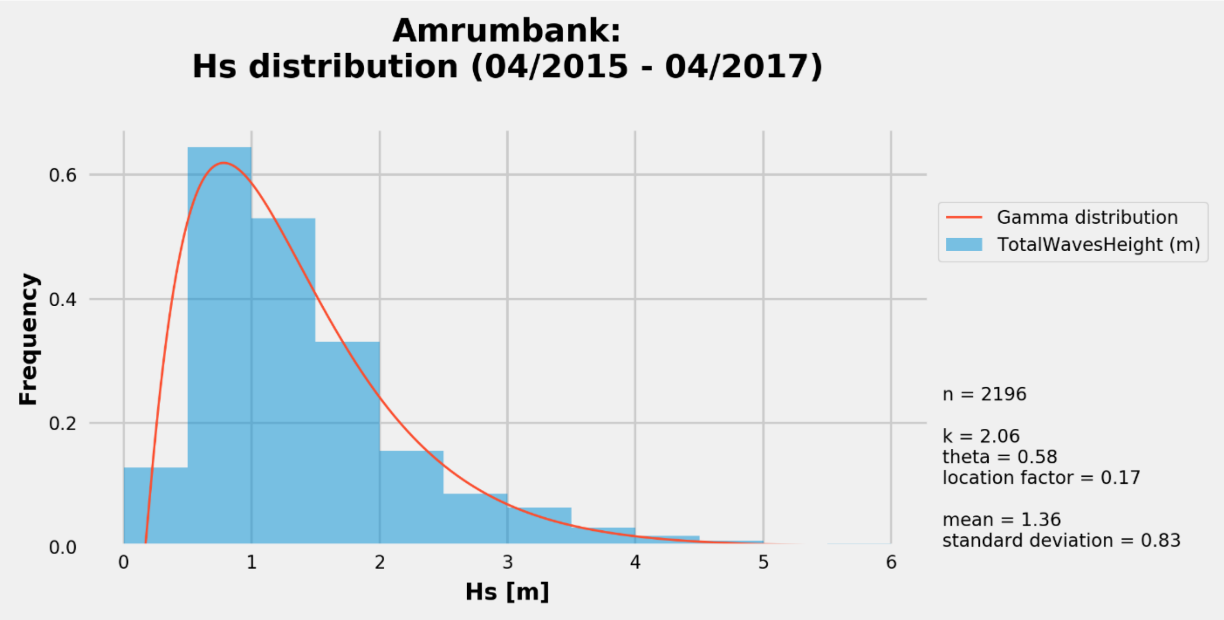

Figure 57: Hs distribution of Amrumbank. Used data from MSG AIS Data Store, figure is own composition.

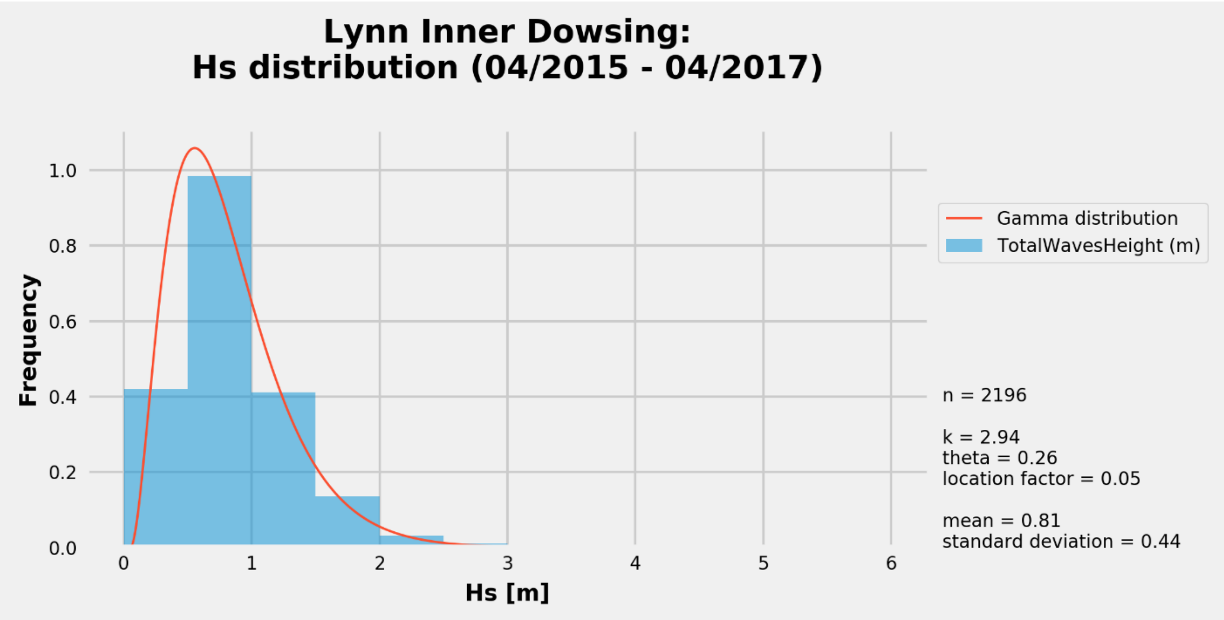

Figure 58: Hs distribution of Lynn Inner Dowsing. Used data from MSG AIS Data Store, figure is own composition.

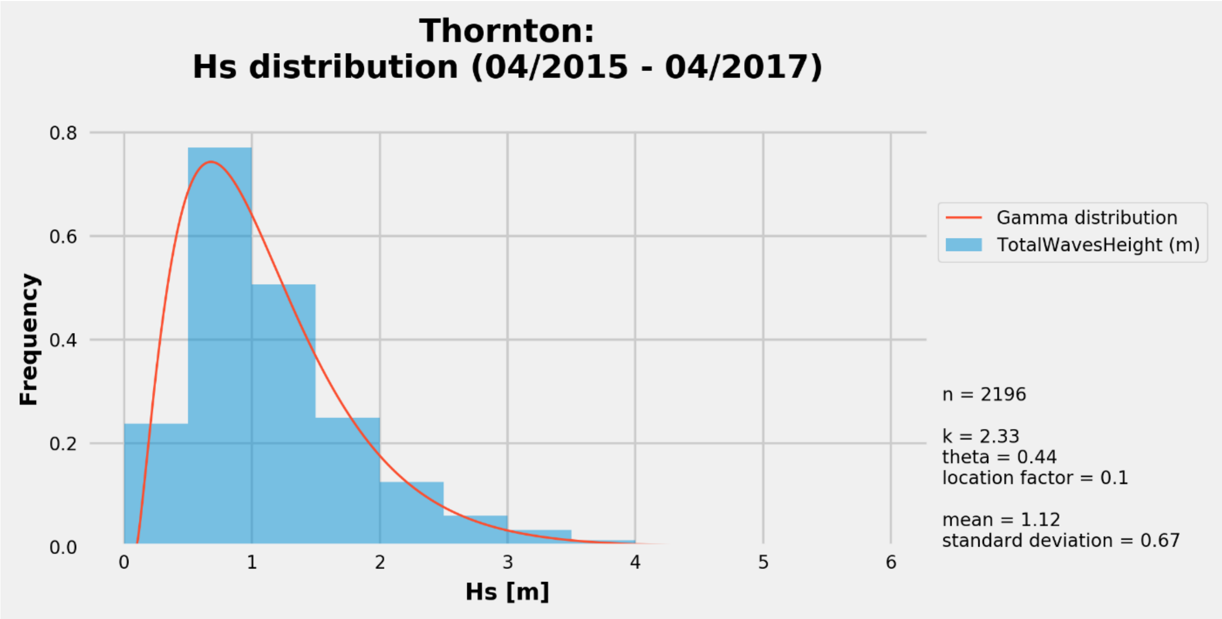

Figure 59: Hs distribution of Thornton. Used data from MSG AIS Data Store, figure is own composition.

Appendix C: Crew Transfer Vessel Charter Contracts & Costs

C.1 Charter Contracts

Wind farm owners/ operators generally charter CTVs to execute CTOs from offshore service providers. Mr Besijn – Commercial Manager of Damen Marine Services – said in an interview that most CTVs are chartered under a time charter contact. Via this contract, wind farm owners/ operators outsource all vessel related issues (Besijn, 2017). 4C Offshore (2016) points out that for the O&M phase two charter lengths are predominant: year-round contracts for planned and preventive maintenance, and short impromptu (months/ weeks/ days) contracts for unplanned corrective maintenance. Furthermore, the CTV charter market is characterised by peaks during summer months and troughs during winter when turbine accessibility is low due to severe weather conditions (Tavner, 2012; 4C Offshore, 2016).

Table 38 includes all known CTV contracts in the selected wind farms over the course of 2016.

Table 38: Known CTV contracts in the selected wind farms over the course of 2016. Data from 4C Offshore (2017b).

Wind Farm	MMSI	Vessel Name	Start Date	End Date
Amrumbank West	209018000	Lina 1	9/16/2014	6/25/2017
Amrumbank West	219015382	FOB SWATH 1	3/5/2016	3/26/2016
Amrumbank West	219016747	MV Assister	3/25/2016	4/21/2016
Amrumbank West	219018788	MV Carrier	7/1/2014	4/15/2017
Amrumbank West	219019852	Kem 1	7/31/2016	8/6/2016
Amrumbank West	219513000	MV Developer	11/26/2014	1/19/2016
Amrumbank West	235095697	Channel Chieftain VI	2/25/2016	2/29/2016
Amrumbank West	235095778	Njord Puffin	5/1/2016	9/27/2016
Amrumbank West	235110913	CWind Artimus	9/19/2016	9/26/2016

Amrumbank West	244630707	OOC Nerz	4/22/2016	10/10/2016
Amrumbank West	244650648	SeaZip 5	4/21/2016	6/14/2016
Amrumbank West	244650648	SeaZip 5	7/19/2016	7/23/2016
Amrumbank West	244650648	SeaZip 5	8/15/2016	9/1/2016
Inner Dowsing	235055752	Windcat 7	3/10/2016	5/28/2016
Inner Dowsing	235055752	Windcat 7	8/21/2016	10/31/2016
Inner Dowsing	235062747	Windcat 9	2/4/2016	3/4/2016
Inner Dowsing	235064453	Windcat 10	1/1/2011	4/15/2016
Inner Dowsing	235068913	Windcat 16	4/18/2016	10/31/2016
Inner Dowsing	235088195	CWind Alliance	7/17/2016	9/23/2016
Inner Dowsing	235097139	CWind Adventure	7/19/2016	8/26/2016
Inner Dowsing	235097407	Windcat 31	5/1/2013	1/23/2017
Lincs	235055752	Windcat 7	6/26/2016	6/28/2016
Lincs	235055752	Windcat 7	7/12/2016	7/29/2016
Lincs	235057789	Windcat 6	9/6/2016	9/13/2016
Lincs	235062747	Windcat 9	12/14/2015	1/19/2016
Lincs	235062747	Windcat 9	3/11/2016	10/31/2016
Lincs	235096027	Windcat 30	12/21/2012	4/15/2017
Lincs	235100258	Windcat 32	8/25/2013	1/26/2017
Lincs	235103062	Windcat 33	3/11/2014	10/31/2016
Lincs	235103062	Windcat 33	12/19/2016	1/23/2017
Lincs	235111112	Dalby Don	3/2/2016	3/3/2016
Lynn	235055752	Windcat 7	3/10/2016	5/28/2016
Lynn	235055752	Windcat 7	6/29/2016	7/1/2016
Lynn	235055752	Windcat 7	8/21/2016	10/31/2016
Lynn	235062747	Windcat 9	2/4/2016	3/4/2016
Lynn	235064453	Windcat 10	1/1/2011	4/15/2016
Lynn	235068913	Windcat 16	4/18/2016	10/31/2016
Lynn	235088195	CWind Alliance	7/17/2016	9/23/2016
Lynn	235088195	CWind Alliance	10/18/2016	11/25/2016
Lynn	235097407	Windcat 31	5/1/2013	1/23/2017

Thornton Bank phase I	253415000	Aquata	12/1/2012	12/10/2016
Thornton Bank phase I	253465000	Arista	9/30/2016	11/1/2016
Thornton Bank phase II	205646000	Aqua Flight	9/20/2016	10/11/2016
Thornton Bank phase II	205678000	Aqualink	3/11/2016	4/25/2017
Thornton Bank phase II	235090843	MCS Sirocco	7/14/2016	8/5/2016
Thornton Bank phase II	235103214	MPI Trifaldi	8/30/2016	10/30/2016
Thornton Bank phase II	235103595	Marineco Stingray	10/15/2016	5/15/2017
Thornton Bank phase II	253465000	Arista	12/19/2016	3/4/2017
Thornton Bank phase III	235068993	MPI Don Quixote	4/1/2016	9/2/2016
Thornton Bank phase III	235085481	MCS Zephyr	6/22/2016	6/22/2016
Thornton Bank phase III	235095777	Njord Petrel	5/12/2016	5/17/2016
Thornton Bank phase III	235095777	Njord Petrel	5/18/2016	6/5/2016
Thornton Bank phase III	235102628	SC Falcon	4/2/2016	6/27/2016
Thornton Bank phase III	235103429	Njord Skua	5/10/2016	5/17/2016
Thornton Bank phase III	235103429	Njord Skua	6/1/2016	6/22/2016

C.2 Costs

The CTV costs for the wind farm owner/ operator includes charter costs and fuel. On top of that, the wind farm owner/ operator must pay the wind turbine technicians that are on-board of the CTV. Other expenses – e.g. hotel costs for the crew between shifts – should be agreed upon in the charter contract and therefore ignored in the further analysis (Dalgic, et al., 2015a; Besijn, 2017).

The daily charter rate for large CTVs similar to a Damen FCS 2610 is in a high market €3,500 - €4,000 per day (Smart, et al., 2016; Besijn, 2017). In the current low market however, charter rates are about a third lower (Besijn, 2017). Fuel costs are strongly dependent on the operational profile, but according to Mr Besijn a rule of thumb is 6 metric tonnes per day (Besijn, 2017). With Rotterdam bunker prices of the start of May 2017, this results in daily fuel costs of approximately €2,350 (Bunker Index, 2017). Based on these rough assumptions, one could say that a large CTV costs a wind farm owner/ operator around €6,000 per day.

According to Smart et al. (2016) a technician costs €100,000 per year. Offshore workers generally work in shifts of 12 hours and are 14 consecutive days on-duty followed by 14 days off-duty. Each technician is on-duty for 24 weeks per year, assuming that they have 4 vacation weeks. This means that a pool of 26 technicians is required if always 12 technicians should be on-duty (most CTVs accommodate 12 technicians), resulting in daily technician costs of €7,123 per CTV.

Appendix D: Crew Transfer Vessel Specifications

Table 39 is a list with specifications form CTVs active in Amrumbank West (AM), Lynn/ Inner Dowsing/ Lincs (LI) or Thornton Phase I/ II/ II over the course of 2016. The CTVs are selected via the in section 5.2.1 described algorithm.

Table 39: Specifications of CTVs active in one of the selected wind farms over the course of 2016. Data from 4C Offshore (2017b).

Wind Farm	MMSI	LOA (m)	Max Speed (kts)	Hull Type	Design	Crane Lift (t)	Max Cargo (t)	Free Deck Space (m2)	Technician capacity
AM	209018000	25	-	SWATH	-	1.6	-	-	24
AM	219015382	25	23	SWATH	S-CAT Ola Lilloe-Olsen / Måløy Verft	1	8	0	24
AM	219016747	19.99	26	Catamaran - Aluminium	0	6.79	15	52	12
AM	219018788	25.75	26	Catamaran - Aluminium	Damen Twin Axe FCS 2610	2.2	15	90	12
AM	219019775	-	-	-	-	-	-	-	-
AM	219019852	28.2	26	Catamaran - Aluminium	Wave Piercing Catamaran CTV	0	18	78	12
AM	219513000	27.2	30	Catamaran - Aluminium	Grovfjord Mek Verksted / Marintek	0.38	20	112	12
AM	235095697	19	25	Catamaran - Aluminium	Catfish Crewcat 19	0	0	0	12
AM	235095778	20.6	26	Catamaran - Aluminium	BMT Nigel Gee	6.5	0	52	12
AM	235110913	22	30	Catamaran - GRP	MPC 22	0	30	144	12
AM	244630707	26.2	27	Catamaran - Aluminium	BMT Nigel Gee NG972	6	0	77	24
AM	244650648	26.3	25	Catamaran - Aluminium	Damen Twin Axe FCS 2610	2.2	0	90	12
AM	244830668	26.3	25	Catamaran - Aluminium	Damen Twin Axe FCS 2610	2.2	0	90	12

LI	235055752	16	27	Catamaran - Aluminium	Mark II	0.44	4	37	12
LI	235057789	16	27	Catamaran - Aluminium	Mark II	0.44	4	37	12
LI	235062747	18	28	Catamaran - Aluminium	Mark III	2	4	28	12
LI	235064453	18	28	Catamaran - Aluminium	Mark III	0.44	4	28	12
LI	235068913	18	28	Catamaran - Aluminium	Mark III	0.44	4	28	12
LI	235075026	18	28	Catamaran - Aluminium	Mark III	0.44	4	28	12
LI	235088195	19	27	Catamaran - GRP	MPC 19	0	16	74	12
LI	235096027	18	28.5	Catamaran - Aluminium	Mark III	0.44	6	36	12
LI	235097139	18.5	28	Catamaran - GRP	MPC 19	0	20	0	12
LI	235097407	18	28.5	Catamaran - Aluminium	MK3 RW	0.44	6	30	12
LI	235100258	18	28.5	Catamaran - Aluminium	Mark III	0.44	6	30	12
LI	235103062	18	28.5	Catamaran - Aluminium	Mark III	0.44	6	36	12
LI	235111112	23	30	Catamaran - Aluminium	Global Marine	0	10	0	12
TH	205646000	14	26	Catamaran - GRP	Blyth Workcat 14m	0	0	0	12
TH	205678000	18.1	23	Catamaran - GRP	Blyth Workcat 18m	0	0	0	12
TH	235068993	20	25	Catamaran - Aluminium	Southboats 20m WFSV	1	10	58	12
TH	235085481	19.2	24	Catamaran - Aluminium	Southboats 18m WFSV	0	10	48	12
TH	235090843	25.75	26	Catamaran - Aluminium	Damen Twin Axe FCS 2610	2.2	15	90	12
TH	235095777	20.6	26	Catamaran - Aluminium	BMT Nigel Gee	6.5	0	52	12
TH	235102628	19	30	Catamaran - GRP	MPC 19	0	16	74	12
TH	235103214	19.15	24	Catamaran - Aluminium	19m GL WFSV	0	10	45	12
TH	235103429	20.6	26	Catamaran - Aluminium	BMT Nigel Gee	6.5	0	52	12

TH	235103595	26.3	25	Catamaran - Aluminium	Damen Twin Axe FCS 2610	0.86	15	90	12
TH	235116836	-	-	-	-	-	-	-	-
TH	253415000	25.75	25	Catamaran - Aluminium	Damen Twin Axe FCS 2610	2.9	12	84	12
TH	253465000	25.75	25	Catamaran - Aluminium	Damen Twin Axe FCS 2610	2.7	12	84	12

Appendix E: Turbine Access Days

E.1 Wind Speed & Mean Significant Wave Height

Each blue dot in Figure 60, Figure 62 and Figure 61 represents one weather forecast for the selected wind farms between April 2015 and April 2017. The data is obtained via MSG. It can be seen in all three figures that the Hs <= 1.5m & Beaufort > 7 quadrant contains no weather forecasts. This means that the 1.5m Hs constraint of CTOs is the binding constraint, as is discussed in section 3.4.2.

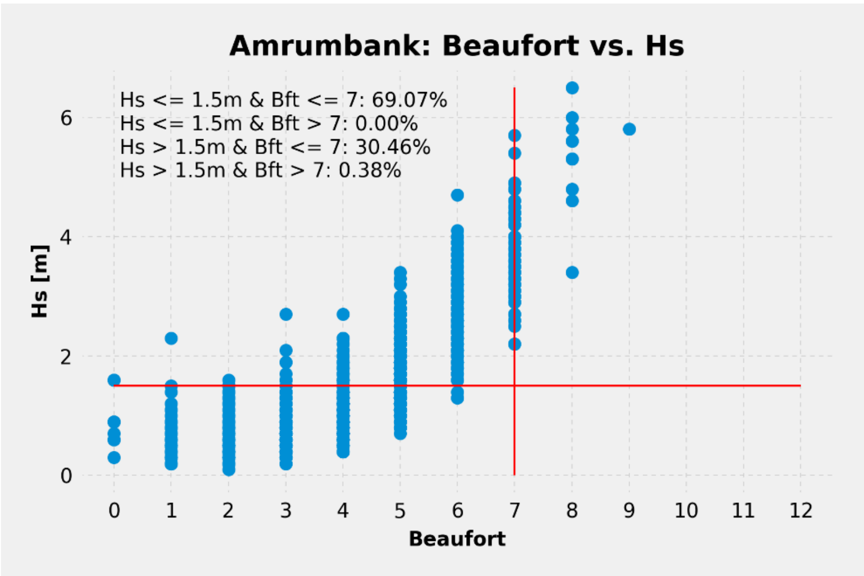

Figure 60: Wind speed vs mean significant wave height of the Amrumbank wind farm. Data from April 2015 till April 2017. Used data from MSG AIS Data Store, figure is own composition.

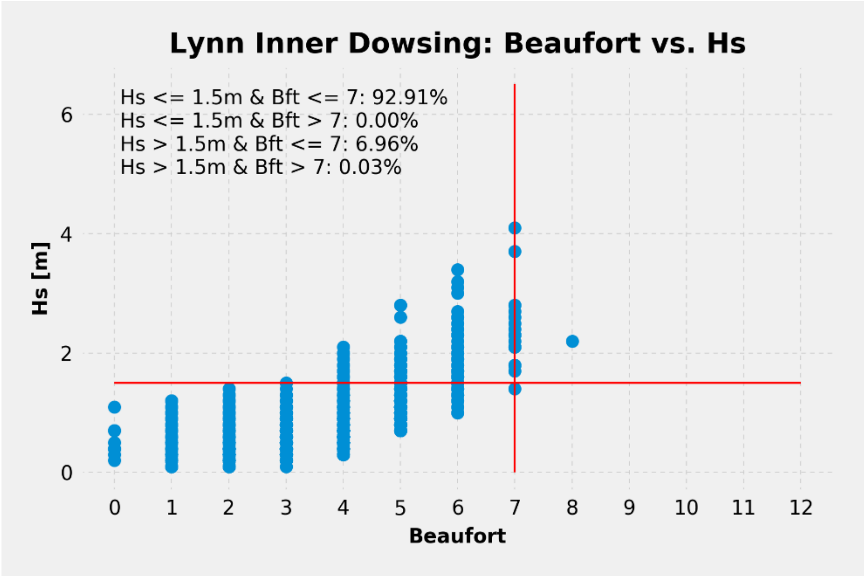

Figure 62: Wind speed vs mean significant wave height of the Lynn Inner Dowsing wind farm. Data from April 2015 till April 2017. Used data from MSG AIS Data Store, figure is own composition.

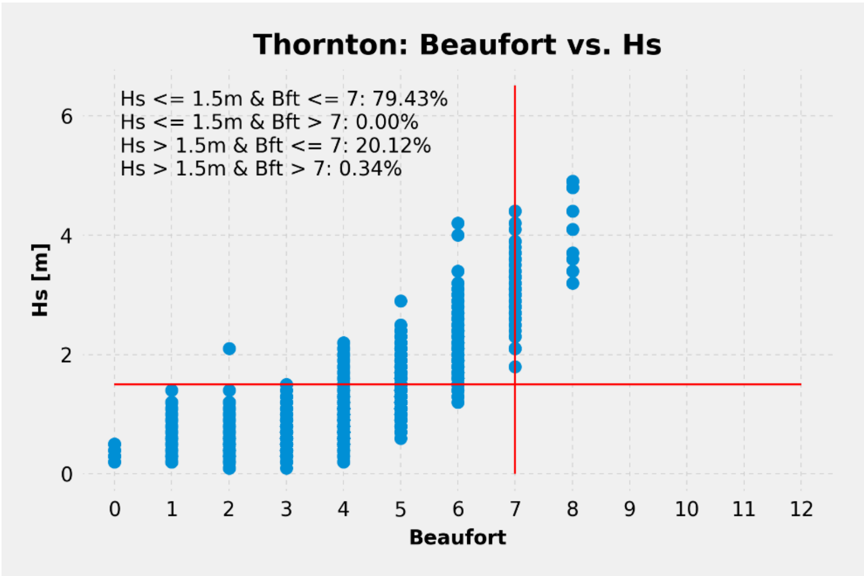

Figure 61: Wind speed vs mean significant wave height of the Thornton wind farm. Data from April 2015 till April 2017. Used data from MSG AIS Data Store, figure is own composition.

E.2 Wind Farm Access Days

Figure 63, Figure 64 and Figure 65 illustrate the number of access days of the selected wind farms. The figures are stacked bar charts showing three elements: full-, half- and no- access days. The figures on top of the bar charts are the number of no access days. Full day access means that the Hs is <= 1.5 m between 6am and 6pm. This means that the Hs in the weather forecasts of 6am, 12pm and 6pm should all be <= 1.5 m, since the Hs is linearly interpolated between the forecasts. Half day access means that the Hs should be <= 1.5 m for at least 6 hours between 6am and 6pm. This means that the Hs should be <= 1.5 m in the weather forecasts of 6am & 12pm or 12pm & 6pm. No access days are the remaining, which means that the Hs >= 1.5 m for the 6am, 12pm and 6pm weather forecasts.

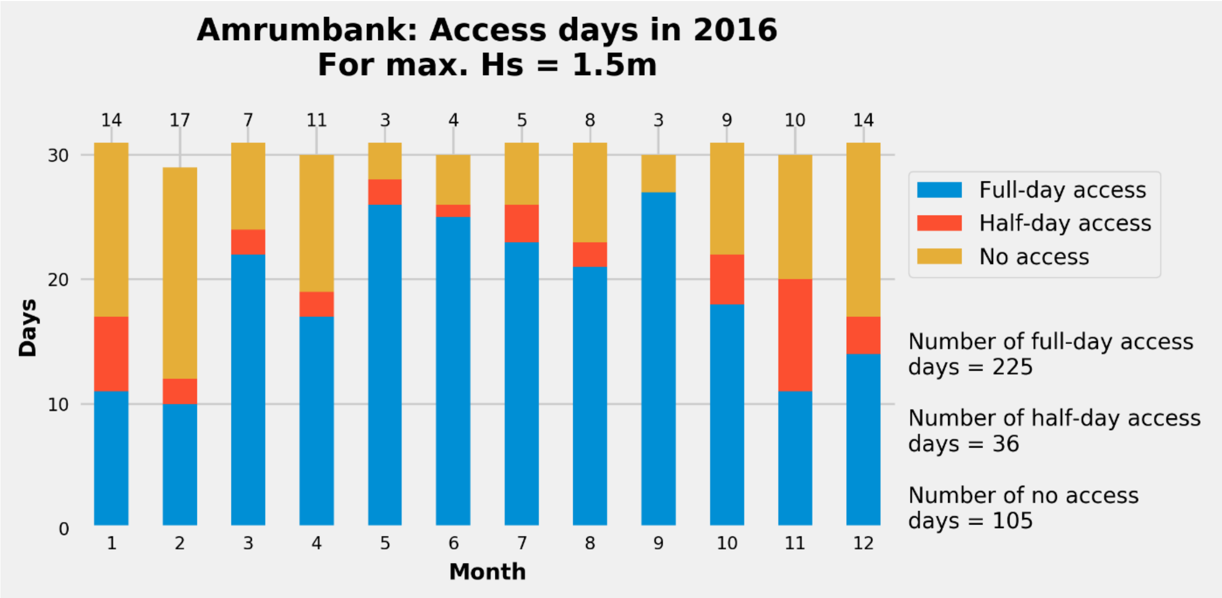

Figure 63: Amrumbank access days in 2016. Used data from MSG AIS Data Store, figure is own composition.

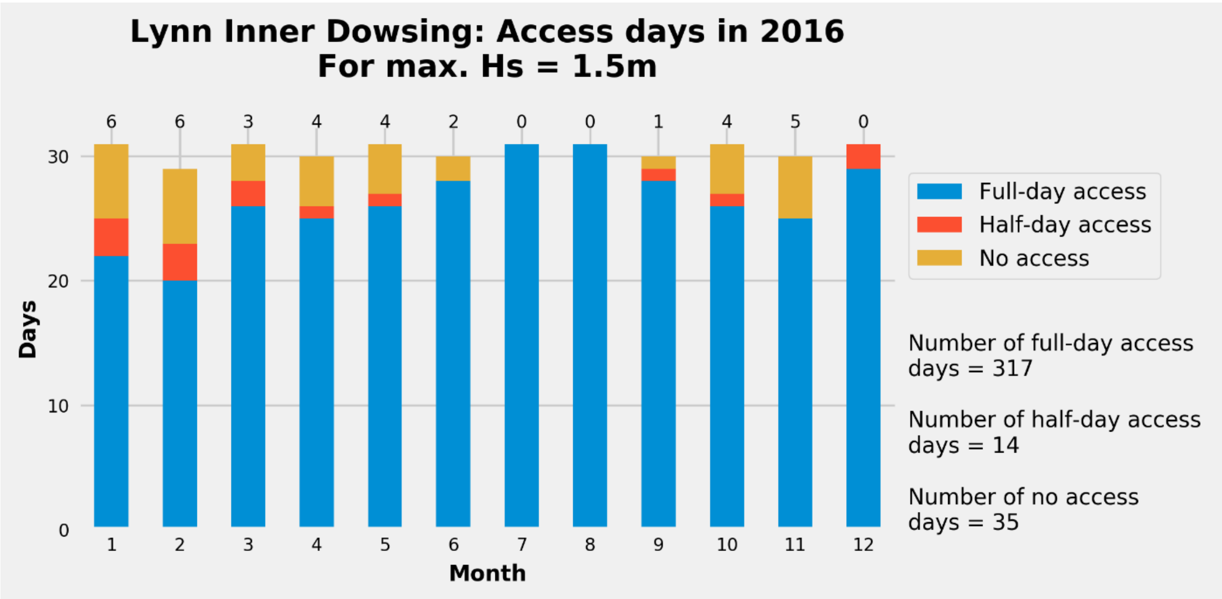

Figure 64: Lynn Inner Dowsing access days in 2016. Used data from MSG AIS Data Store, figure is own composition.

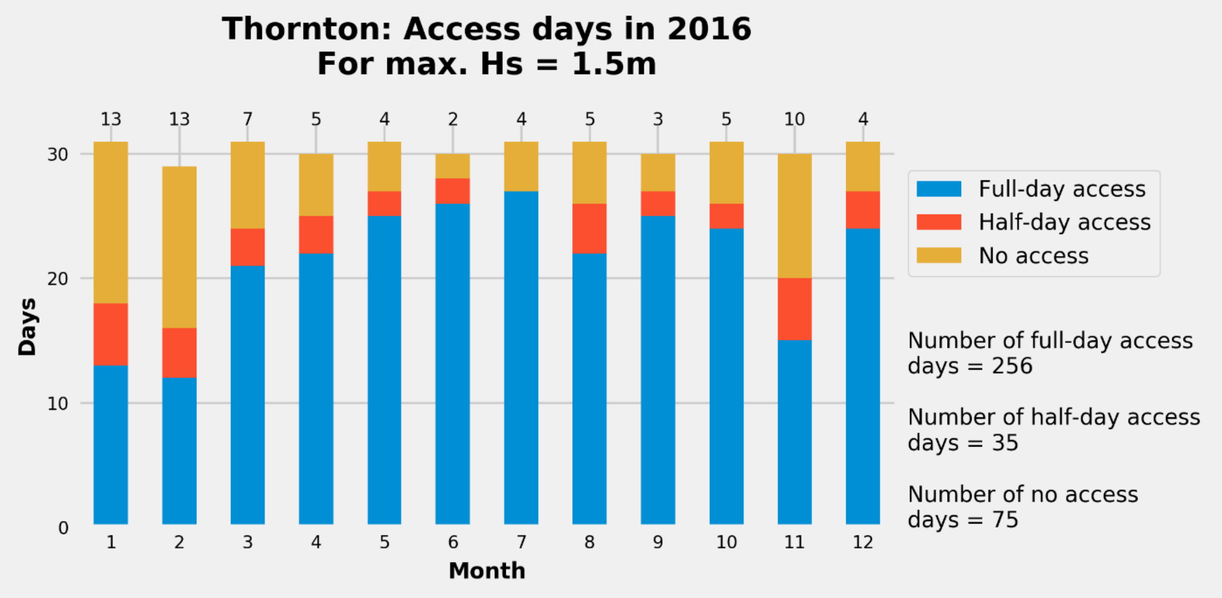

Figure 65: Thornton access days in 2016. Used data from MSG AIS Data Store, figure is own composition.

Appendix F: Time Deltas of In-Field Automatic Identification System Data

This appendix includes the CDF of time deltas between consecutive AIS reports of in-field data for Amrumbank and Lynn Inner Dowsing. Furthermore, the distribution of the total time per time delta category is presented.

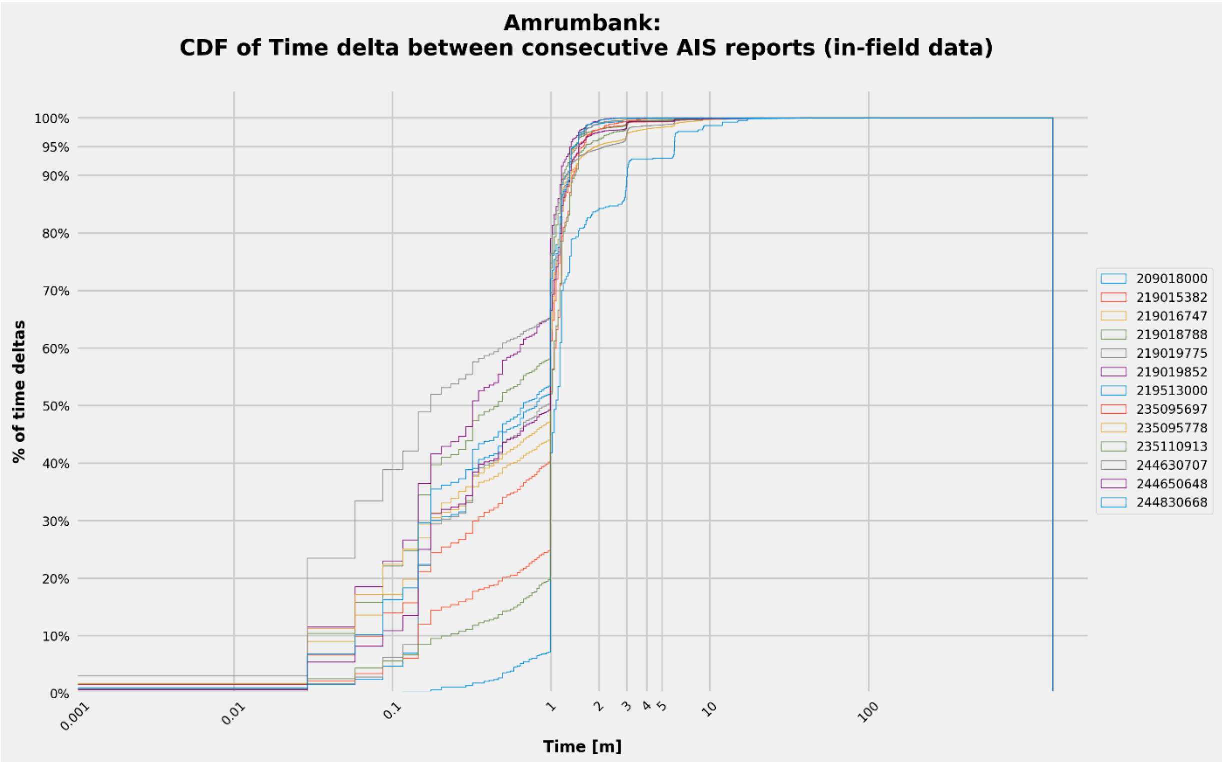

Figure 66: Cumulative Distribution Function of time deltas of in-field AIS data of all CTVs operative in Amrumbank in 2016. Used data from MSG AIS Data Store, figure is own composition.

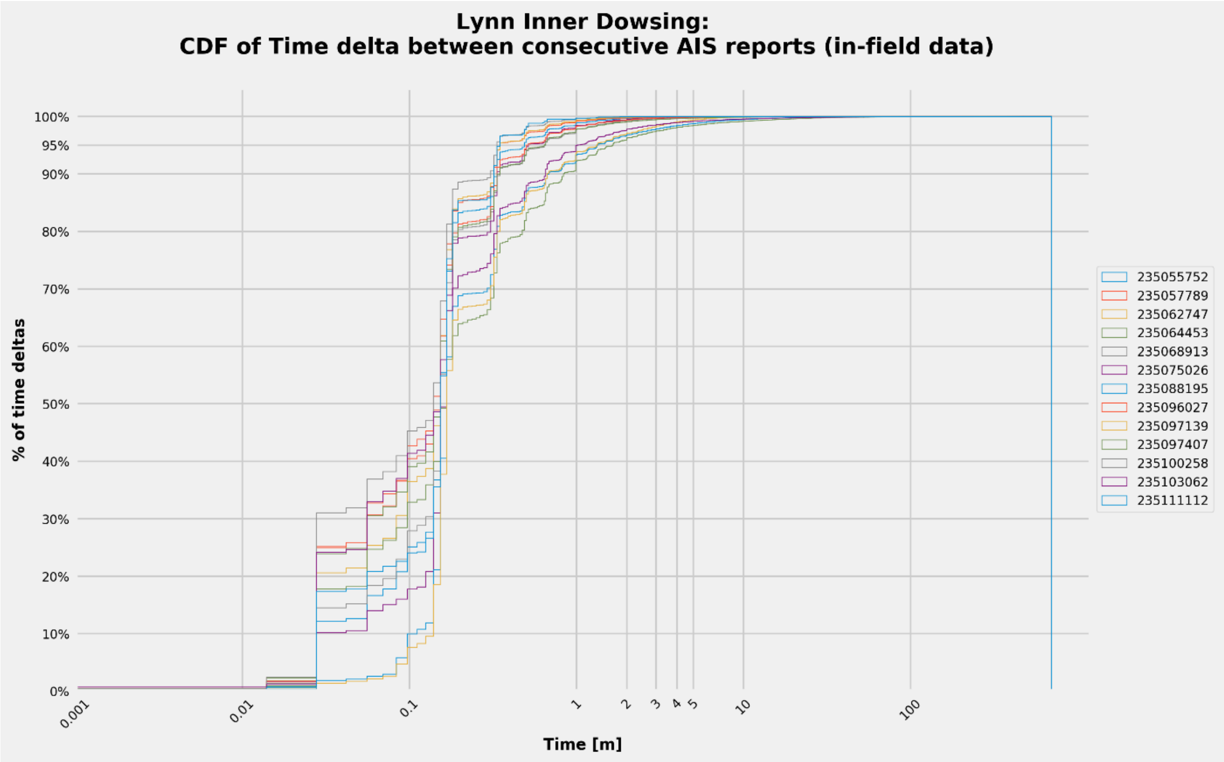

Figure 68: Cumulative Distribution Function of time deltas of in-field AIS data of all CTVs operative in Lynn Inner Dowsing in 2016. Used data from MSG AIS Data Store, figure is own composition.

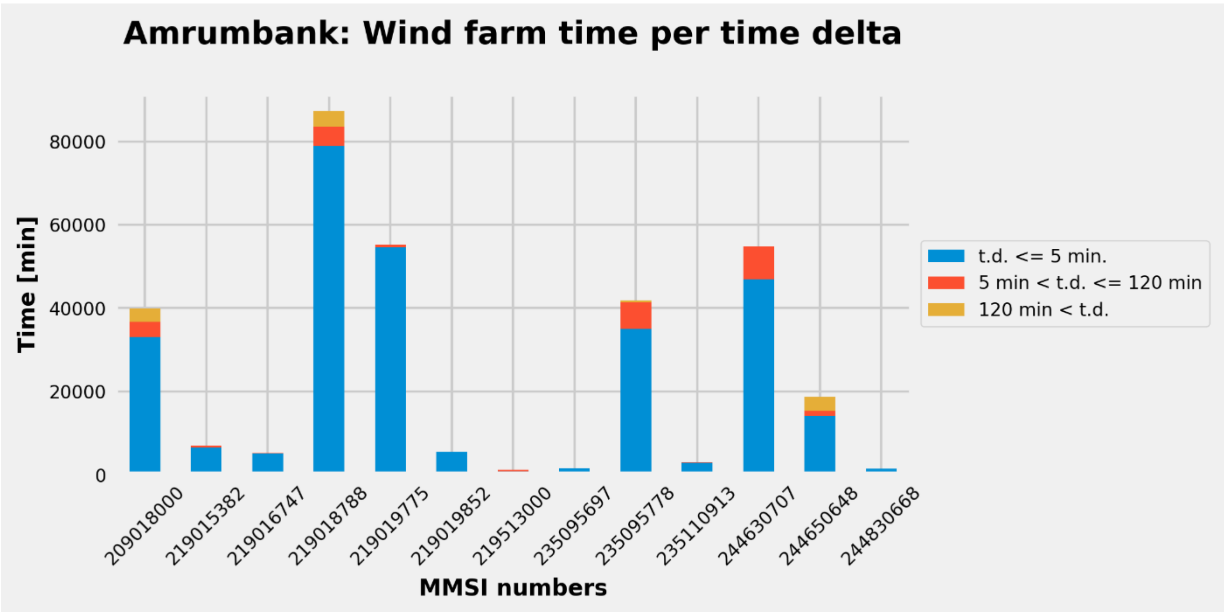

Figure 67: Distribution of wind farm time per time delta category in Amrumbank. Source: own composition.

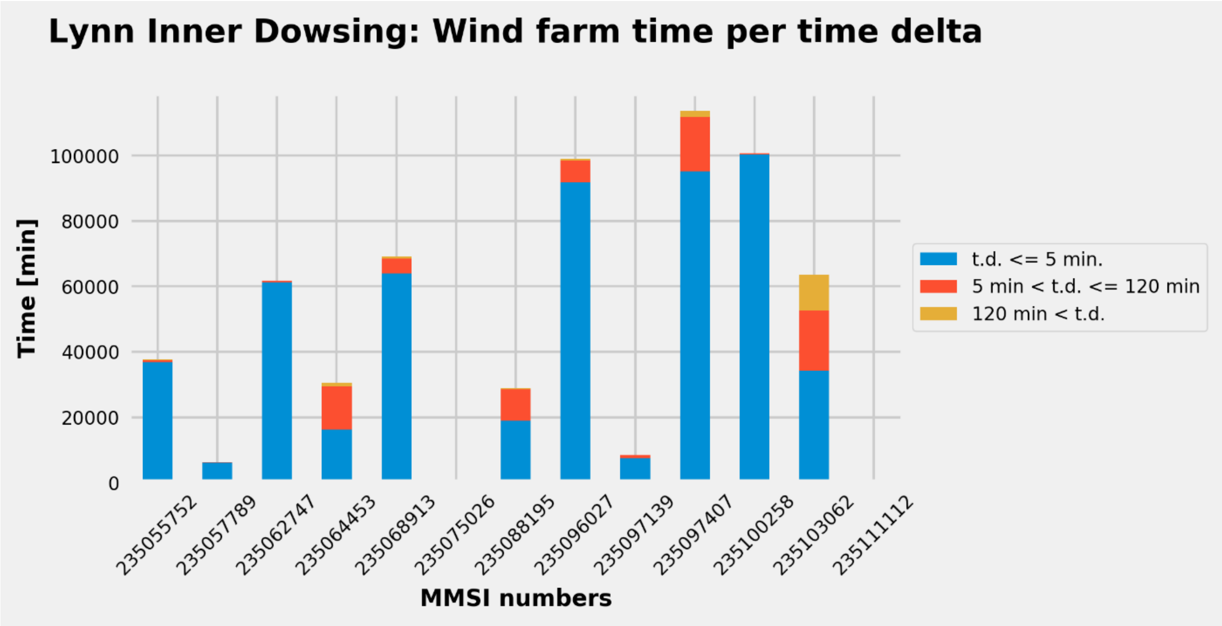

Figure 69: Distribution of wind farm time per time delta category in Lynn Inner Dowsing. Source: own composition.

Appendix G: Validation of Crew Transfer Operation Algorithm

This appendix includes the CTO algorithm validation results for the tested settings. In total, the algorithm output is tested for four CTVs over a period of one week (2 CTVs for Amrumbank, 1 CTV for Lynn Inner Dowsing and 1 CTV for Thornton). The results of the first CTV are included in section 6.2.1.

Table 40: CTO algorithm validation results for Amrumbank, MMSI 219018788, period 5/7/16 – 5/13/16. Source: own composition.

Algorithm	Transfers counted	Correctly counted	Not counted	Counted double	Erroneously counted	Turbine locations	Max SOG [kts]	Max turbine distance [m]	Min transfer time [min]	Adding missing turbine ID labels [up to x rows]	F1-score
Validation	**76**	-	-	-	-	-	-	-	-	-	-
7	77	76	0	0	1	DBSCAN	1	75	1	5	99.3%
8	77	76	0	0	1	DBSCAN	1	70	1	5	99.3%
9	77	76	0	0	1	DBSCAN	1	65	1	5	99.3%
10	76	76	0	0	0	DBSCAN	1	60	1	5	100.0%
17	77	76	0	0	1	DBSCAN	1	70	1	7	99.3%
18	76	76	0	0	0	DBSCAN	1	70	1	9	100.0%
19	76	76	0	0	0	DBSCAN	1	70	1	11	100.0%
20	76	76	0	0	0	DBSCAN	1	65	1	9	100.0%
21	76	76	0	0	0	DBSCAN	1	65	1	11	100.0%
A	72	72	4	0	0	Grid outlook	1	65	1	5	99.3%
B	75	75	1	0	0	Grid outlook	1	70	1	5	99.3%

Table 41: CTO algorithm validation results for Lynn Inner Dowsing, MMSI 235062747, period 6/6/16 - 6/12/16. Source: own composition.

Algorithm	Transfers counted	Correctly counted	Not counted	Counted double	Erroneously counted	Turbine locations	Max SOG [kts]	Max turbine distance [m]	Min transfer time [min]	Adding missing turbine ID labels [up to x rows]	F1-score
Validation	**94**	-	-	-	-	-	-	-	-	-	-
7	99	94	0	3	2	Heat-map	1	75	1	5	97.4%
8	99	94	0	3	2	Heat-map	1	70	1	5	97.4%
9	98	94	0	3	1	Heat-map	1	65	1	5	97.9%
10	98	94	0	3	1	Heat-map	1	60	1	5	97.9%
17	98	94	0	4	0	Heat-map	1	70	1	7	97.4%
18	97	94	0	3	0	Heat-map	1	70	1	9	97.9%
19	94	94	0	0	0	Heat-map	1	70	1	11	98.4%
20	96	94	0	2	0	Heat-map	1	65	1	9	100.0%
21	94	94	0	0	0	Heat-map	1	65	1	11	98.4%

Table 42: CTO algorithm validation results for Thornton, MMSI 253515000, period 5/7/16 - 5/13/16. Source: own composition.

Algorithm	Transfers counted	Correctly counted	Not counted	Counted double	Erroneously counted	Turbine locations	Max SOG [kts]	Max turbine distance [m]	Min transfer time [min]	Adding missing turbine ID labels [up to x rows]	F1-score
Validation	**57**	-	-	-	-	-	-	-	-	-	-
7	60	57	0	1	2	DBSCAN	1	75	1	5	97.4%
8	59	57	0	0	2	DBSCAN	1	70	1	5	98.3%
9	59	57	0	0	2	DBSCAN	1	65	1	5	98.3%
10	57	56	1	0	1	DBSCAN	1	60	1	5	98.2%
17	58	57	0	0	1	DBSCAN	1	70	1	7	99.1%
18	58	57	0	0	1	DBSCAN	1	70	1	9	99.1%
19	58	57	0	0	1	DBSCAN	1	70	1	11	99.1%
20	58	57	0	0	1	DBSCAN	1	65	1	9	99.1%
21	58	57	0	0	1	DBSCAN	1	65	1	11	99.1%

Appendix H: Crew Transfer Operation Demand

The figures shown in this appendix are histograms and their corresponding probability distributions of the number of transfers executed at each turbine for the Amrumbank, Lynn Inner Dowsing and Thornton over the year 2016.

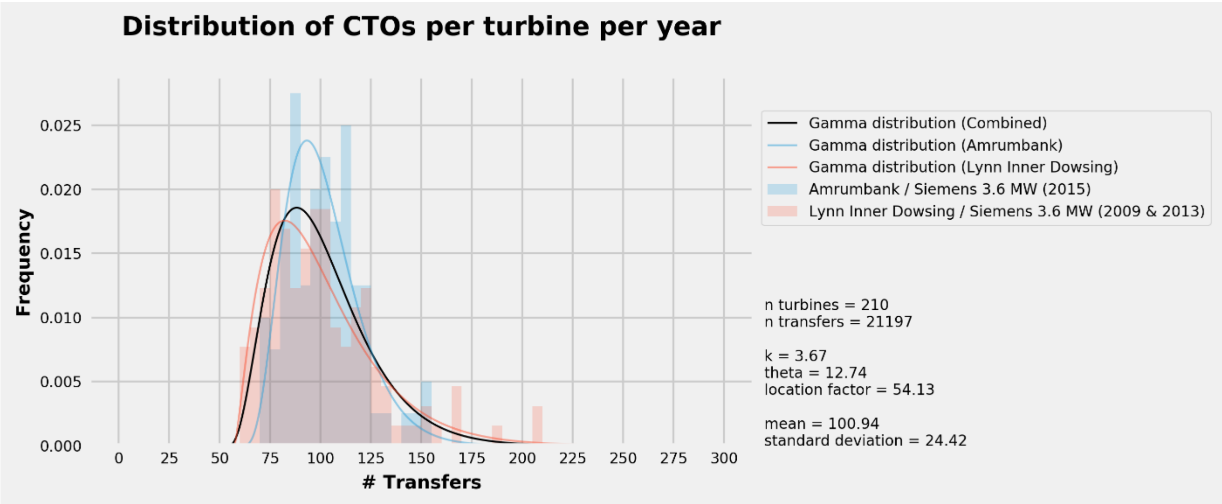

Figure 70: Distribution of transfers per turbine of Siemens turbines in Amrumbank and Lynn Inner Dowsing in 2016. Source: own composition.

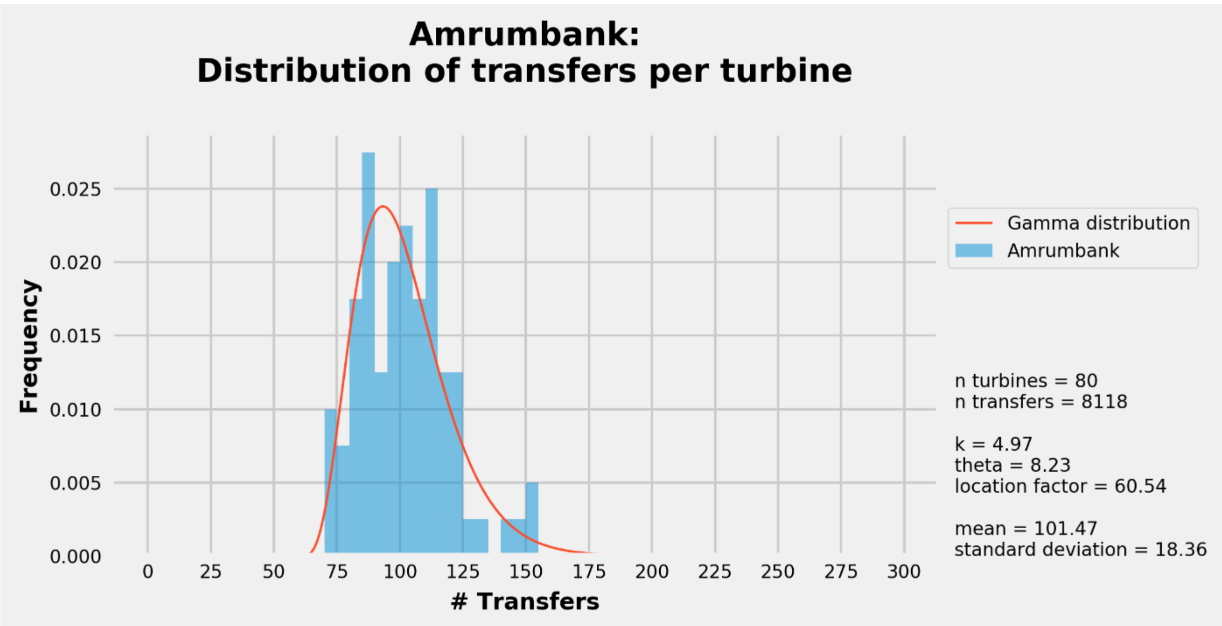

Figure 71: Distribution of transfer per turbine of Amrumbank in 2016. Source: own composition.

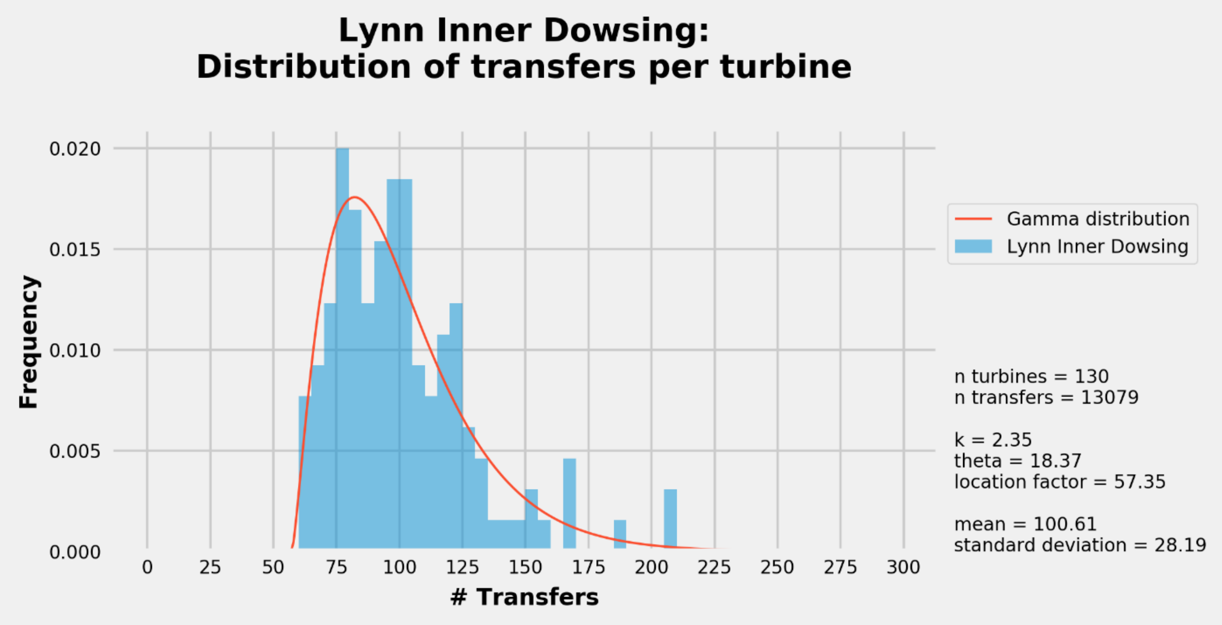

Figure 72: Distribution of transfer per turbine of Lynn Inner Dowsing in 2016. Source: own composition.

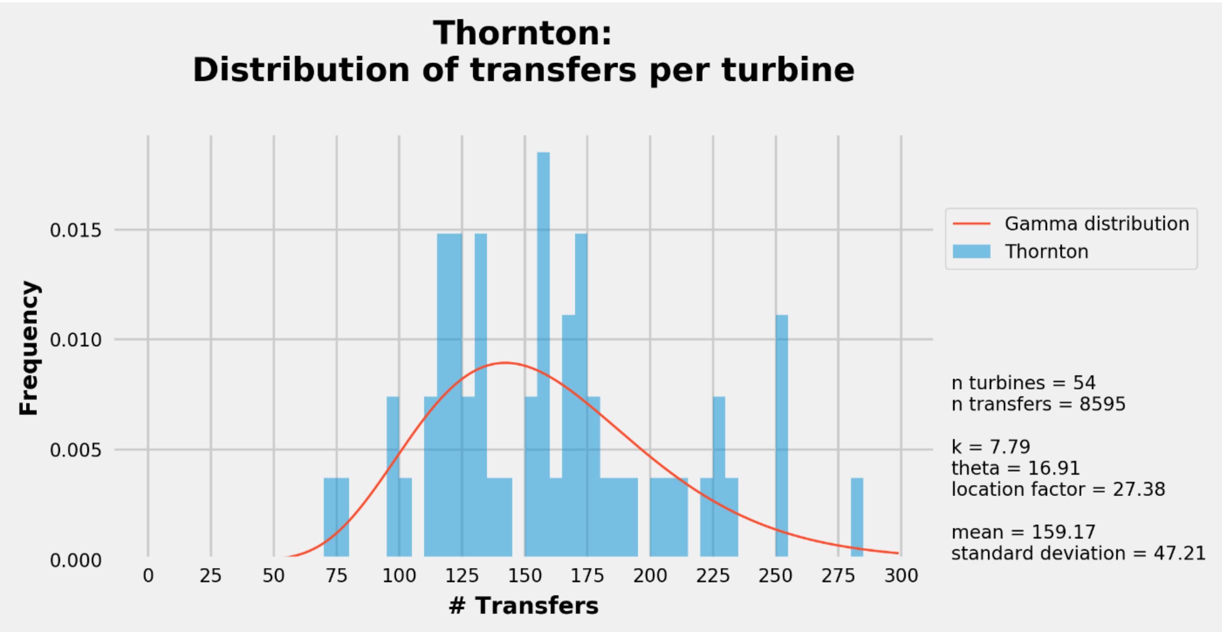

Figure 73: Distribution of transfer per turbine of Thornton in 2016. Source: own composition.

Appendix I: Port & Wind Farm Days

I.1 Mean Significant Wave Height During Port & Wind Farm Days

The mean Hs distributions during port and wind farm days are show in this section. It can be noticed that for the wind farm days a mean Hs of more than 1.5 m is extremely rare. For the port days there is not such a clear Hs boundary. This may be caused due to the fact that there are more reasons for a CTV to stay in port apart from wind farm non-access days.

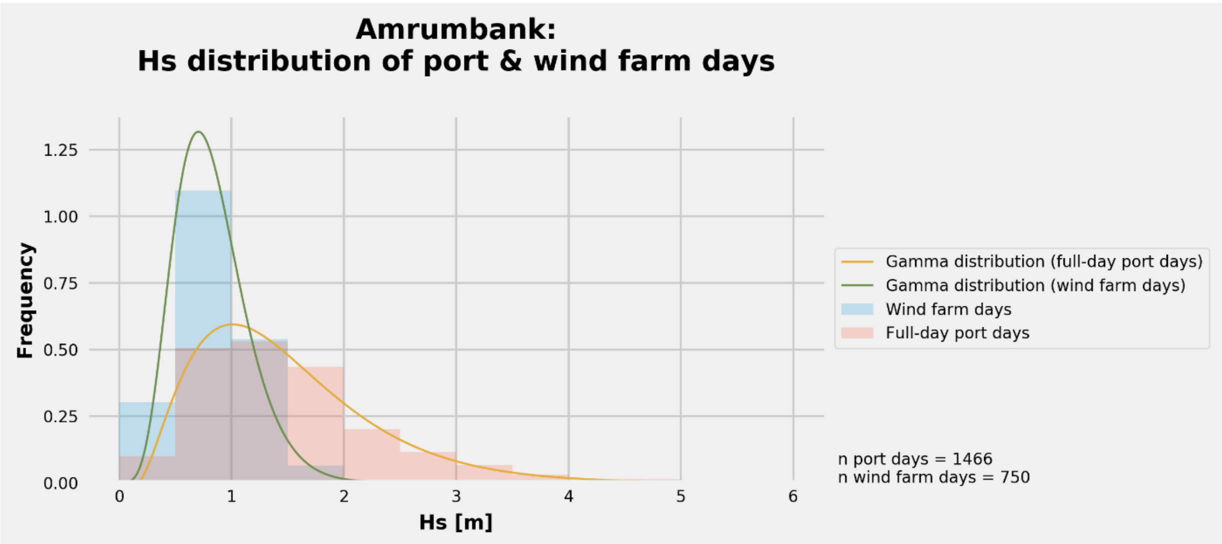

Figure 74: Hs distribution for port and wind farm days for Amrumbank. Source: own composition.

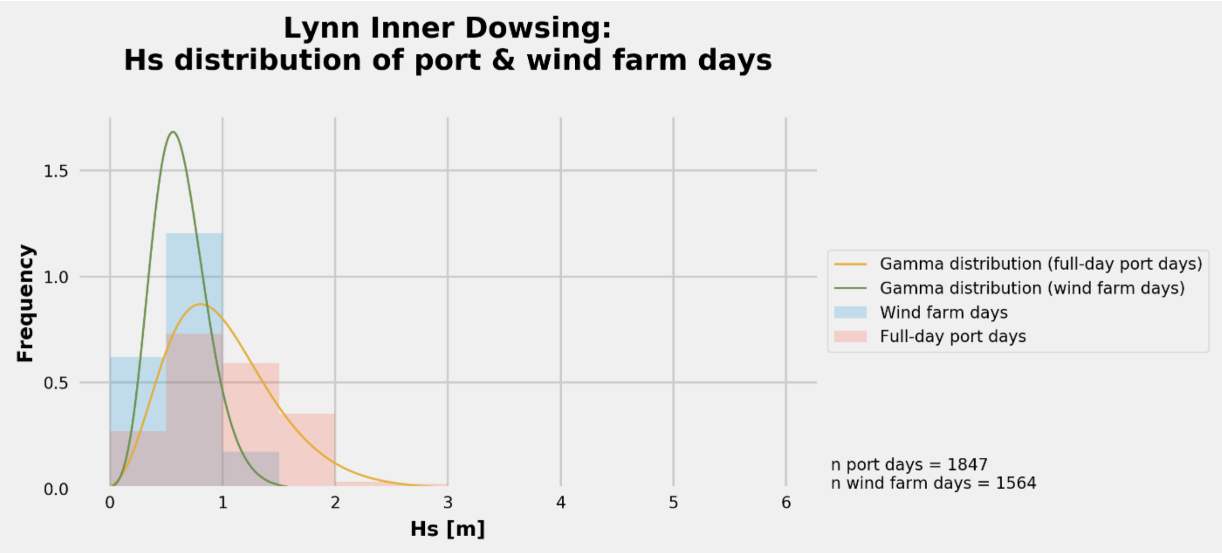

Figure 75: Hs distribution for port and wind farm days for Lynn Inner Dowsing. Source: own composition.

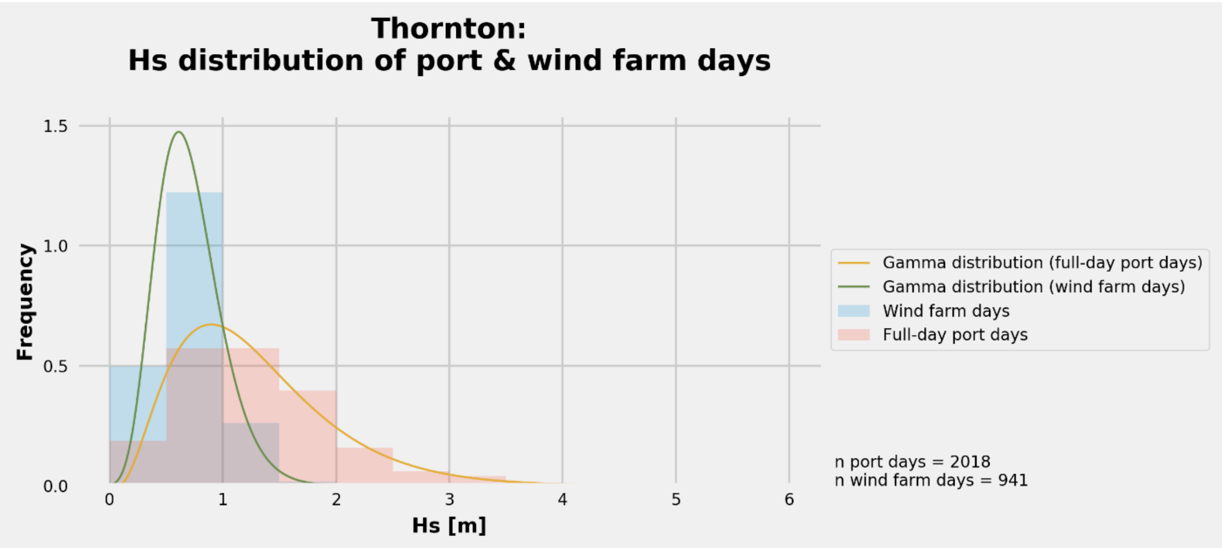

Figure 76: Hs distribution for port and wind farm days for Thornton. Source: own composition.

I.2 Utilisation of Crew Transfer Vessels

The tables included in this section show the utilisation of CTVs based on the mean number of CTV working days per vessel, the mean number of CTVs active in the wind farm and the wind farm accessibility.

The mean number of CTV working days conducted per vessel is calculated by dividing the number of CTV working days by the mean number of CTVs working in the wind farm. This number can be used to calculate the percentage of wind farm days. The percentage of wind farm days, together with the wind farm accessibility is used to calculate the CTV utilisation. If the CTVs worked on days for which the Hs was higher than 1.5 m, the CTV utilisation could be higher than 100%

Table 43: CTV utilisation of the CTVs operative in Amrumbank in 2016. Source: own composition.

	Percentage of wind farm day	Percentage of wind farm access days	CTV utilisation
Jan	51.6%	59.3%	87.0%
Feb	37.9%	47.4%	80.1%
Mar	77.4%	76.9%	100.7%
Apr	66.7%	74.2%	89.8%
May	87.1%	81.2%	107.3%
Jun	83.3%	85.6%	97.4%
Jul	77.4%	77.4%	100.0%
Aug	74.2%	84.4%	87.9%
Sep	86.7%	78.3%	110.6%
Oct	58.1%	76.9%	75.5%
Nov	50.0%	44.4%	112.5%
Dec	35.5%	40.8%	87.1%
Average			**94.7%**

Table 44: CTV utilisation of the CTVs operative in Lynn Inner Dowsing in 2016. Source: own composition.

	Percentage of wind farm day	Percentage of wind farm access days	CTV utilisation
Jan	61.3%	85.3%	71.8%
Feb	61.3%	84.2%	72.8%
Mar	77.4%	95.2%	81.4%
Apr	71.0%	94.3%	75.2%
May	71.0%	93.0%	76.3%
Jun	80.6%	96.7%	83.4%
Jul	100.0%	98.9%	101.1%
Aug	96.8%	100.0%	96.8%
Sep	90.3%	95.0%	95.1%
Oct	51.6%	90.9%	56.8%
Nov	58.1%	86.7%	67.0%
Dec	90.3%	91.3%	98.9%
Average			**81.4%**

Table 45: CTV utilisation of the CTVs operative in Thornton in 2016. Source: own composition.

	Percentage of wind farm day	Percentage of wind farm access days	CTV utilisation
Jan	38.7%	67.2%	57.6%
Feb	41.9%	67.8%	61.8%
Mar	64.5%	79.6%	81.1%
Apr	64.5%	87.1%	74.1%
May	87.1%	82.8%	105.2%
Jun	80.6%	90.0%	89.6%
Jul	87.1%	87.6%	99.4%
Aug	67.7%	86.0%	78.8%
Sep	83.9%	84.4%	99.3%
Oct	74.2%	89.2%	83.1%
Nov	45.2%	54.4%	82.9%
Dec	80.6%	73.9%	109.1%
Average			**85.2%**