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Assessing Offshore Wind Farm Collision Risks using AIS data: An Overview

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Purpose: *Currently offshore wind farms are built in areas with high vessel traffic like the German Economic Exclusive Zone (EEZ). During the building phase and the operational phase a high amount of vessels will pass these offshore wind farms in close proximity and thus there is a risk of collision of a vessel with other vessels in the wind farms, e.g. installation vessels or service vessels or with objects like the wind turbines or the substation of an offshore wind farm.*

Methodology: *In this paper relevant publications over the last ten years with a focus on the use of AIS (Automated Identification System) in regard to the collision risks of offshore wind farms will be investigated and sorted in a structured way. The publications will then be listed and classified into six sub groups.*

Findings: *This analysis will show an overview of the current state of the art in using AIS data to determine the collision risks for offshore wind farms and the proposed methods to reduce these risks.*

Originality: *The paper is original because there is currently no complete and up-to-date overview for the use of AIS-data to mitigate the collision risks of vessels with offshore wind farms.*

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1 Introduction

Offshore Wind is becoming more feasible over time and due to technical advances as well as political decisions the amount of offshore wind turbines in the Exclusive Economic Zones (EEZ) in the North and the Baltic Seas of the Federal Republic of Germany will increase from 1.469 turbines with 7.5 GW in 2019 to 30 GW by 2030. Due to recent political events it is possible that the as of today announced numbers will even increase more.

But not only the number of offshore wind turbines will increase in German territorial waters but also the amount of vessels which will be traversing the German EEZ. The German Bight for example is already one of the most frequented water areas in the world.

The constant increase of offshore wind farms in the German EEZ and a simultaneous expansive increase of European maritime traffic and ship size developments in recent years lead to an increasing safety risk due to limited available fairways. Last but not least, these increasing frequencies can lead to direct collisions between offshore wind turbines and ships or other accidents. As an example, in the area of the southwestern Baltic Sea, 1520 reported shipping accidents occurred in the period 2011-2015 with a level of about 300 accidents per year. The German Bight of the North Sea is one of the most frequented maritime sea routes in the world.

Human error is responsible for most collision accidents. 95% off all accidents between 2015 and 2020 in Korean waters for example were caused by human error (Park et al. 2021).

(Copping et al. 2016) states that because of "[…] the development of offshore wind farms, fixed structures will begin to appear in and around historical shipping lanes." This shows the importance of the topic and thus the relevance to investigate this topic further.

2 Problem description

Since these conditions are very complex and thus can lead to accidents between ships and offshore wind structures like substations or the offshore wind turbines or to accidents between two ships in the wind farm or close to the wind farm with adverse effects on human lives, the environment or high financial losses it is necessary to mitigate these risks.

In this paper the authors will give an overview over the current scientific literature in regard to the use of AIS-data to access and mitigate collision risks for offshore wind farms.

Due to the new and applied nature of this topic a lot of the literature is “grey literature” from companies as well as internet sources by companies. Additionally standards and guidelines are also present, e.g. (Wasserstraßen- und Schifffahrtsverwaltung des Bundes 2021). Additional basic literature like books are also sources which will not be considered in this paper.

2.1 Navigational Safety / Collision Risks

In the German EEZ in the North Sea and Baltic Sea and thus also in German shipping lanes, offshore wind farms and offshore platforms have been already constructed and in the foreseeable future even more will be built. From the point of view of nautical traffic and maritime policy, such installations constitute artificially created obstacles to navigation, which restricts the free sea space and thus creates new hazards for the safety and ease of shipping traffic. These risks have to be mitigated by appropriate measures. This also applies to the laying and operation of submarine cables and comparable submarine installations in traffic-relevant areas.

Ensuring the safety and ease of shipping traffic is governed by international and national regulations and is an explicit part of the "Strategy of the Federal Government for the Utilization of Wind Energy at Sea" from 2002.

The responsibility for both the prevention of dangers to the safety and ease of shipping lies with the Federal Maritime Administration pursuant to § 1(2) in conjunction with §3(1) of the Seeaufgabengesetz - SeeAufgG (Wasserstraßen- und Schifffahrtsverwaltung des Bundes 2021). Offshore windfarms have to be equipped with AIS-transponders in the German EEZ meaning that at least all of the outer wind turbines have to be fitted with AIS-transponders (Wasserstraßen- und Schifffahrtsverwaltung des Bundes 2021).

Additionally in the planning phase of an offshore wind farm there is the obligation to do an NRA (Navigational Risk Assessment) by the developer to be aware of potential nautical risks and thus mitigate the risks of collisions. This NRA is not standardized so that there are different approaches.

The following overview shows what are the influencing factors on navigational risks in offshore wind parks:

(Lv et al. 2021) give a very good overview over these influencing factors. They divide them into “natural conditions” and “navigational environment”. Whereas in the first, visibility, wind speed and wind direction, current speed and current direction are the determining factors. The factors in the “navigational environment” are distance between navigational routes and the wind farm. Additionally the amount of traffic as well as the number of encounter areas are of importance, too.

2.2 Automated Identification AIS

„The AIS (Automated Identification System) is a real-time network of transmitters and receivers that allow vessel movements to be broadcast, tracked, and recorded.” (Wright et al. 2019).

The International Maritime Organization (IMO) requires since 31 December 2004 in SOLAS (Safety on Life at Sea) regulation V/19 that all vessels of 300 gross tonnage and above in international voyages and all vessels above 500 gross tonnage in non-international voyages as well as all passenger vessels to be equipped with AIS (IMO 2022).

Additionally to its traditional role use of mitigating collisions by keeping track of vessels, AIS is also used for maritime safety planning (Wright et al. 2019). This could be for example, the planning to reduce accidents between vessels and offshore structures (like offshore wind farms) before they are build.

By using AIS heat maps, historical AIS data is used to determine where ships in general travel (Wright et al. 2019). This information can be used in the planning process of the construction of an offshore wind farm. Additionally real-time AIS data can be used to determine the behavior of a ship (Wright et al. 2019) and thus to mitigate the collision risk on an operative level. Interestingly only 75% of all commercial vessels are fitted with AIS (Natale et al. 2015). Since it is only mandatory for vessels over 15m in length.

The following table 1 gives an overview over the information which are send by AIS systems.

Table 1: AIS Information Source (IALA 2014)

Static information	Dynamic Information	Voyage related information
MMSI (Maritime Mobile Service Identity)	Ships's position	Ships's draught
Call Sign and ship name	Position time stamp in UTC	Hazardous cargo (type)
IMO Number	Course over ground (COG)	Destination ETA (Estimated time of Arrival)
Length and beam	Speed over ground (SOG)	
Type of vessel	Navigational status (underway, at anchor, moored)	
Location of position fixing antenna	Rate of turn (ROT)	

(Wawruch and Stupak 2011) give a good overview in their paper which input data from AIS-sources can and should be used to construct a model (see table 2).

Table 2: AIS input data for a model (Wawruch and Stupak 2011)

Wind farm data	**Wind turbine positions, distances between the wind turbines, tower dimensions**
Data wind farm location	Shape of the coast line, water depths, ground, sea level changes (e.g. tides)
Information about ship movements	Ship routes, density of traffic, vessel types, changes in vessel traffic based on season or day
Wind and waves	Speed and direction of wind, wave height, wave direction, speed of current, visibility, ice conditions
Technical vessel data	e.g. frequency of engine damage, possible tug assistance
Additional information	Probabilities of human error during planning of voyage, possible navigational errors

(Wawruch and Stupak 2011) additionally name models which were developed by organizations dealing with shipping safety: COLLIDE by Safetec Nordic AS, the models by the Dutch Maritime Research Institute MARIN (SOCRA – Ship Offshore platform Collision Risk Assesment and SAMSON – Safety Assessment Models for Shipping and Offshore in the North Sea); CRASH (Computerized Risk Assessment and MARCS (Marine Accident Risk Calculation System) by Det Norske Veritas; COLWT by Germanischer Lloyd; COLLRISK by Anatec UK Ltd. and DYMITRI by British Maritime Technology (BMT).

According to the UN Convention of the Law of the Sea (UNCLOS) vessels which are restricted in their maneuvering by obstacles like an offshore wind farm have a mandatory safety zone of 500 m around them (United Nations 1982).

3 Research Methodology

3.1 Literature Review

In this chapter a structured literature review for AIS as a tool to mitigate the collision risks for offshore wind turbines was conducted. The goal is to give a concise overview over the relevant publications.

In this paper the emphasis lies on peer reviewed scientific papers . In addition books and book chapters were not included in this paper. Grey literature and internet sources were also not taken into account. Thus only peer-reviewed articles from journals and conference proceedings were considered for this paper. Only publications in English were reviewed. To not miss relevant publications the snowballing was used (Wohlin 2014).

The databases used for the search were: Google Scholar, Scopus and Web of Science. The time frame were the publications were considered was January 2010 till March 2022.

The following keyword / terms were used in the search: AIS, Offshore Wind, Collision Model.

The search string: “AIS”, “Offshore Wind”, “Collison Model” returned 489 publications in Google Scholar. The next step was reading the titles if they fit the scope of this literature research. After this step 158 papers came into deeper consideration. Then the abstracts of these papers were read and the papers which were deemed useful after this step were investigated further. Thus the final sample of 23 were archived for Google Scholar. The procedure was then repeated for the other two databases. After analyzing the three databases and elimination of duplicates a total of 25 relevant papers were the result. These publications are shown in Tab. 3.

3.2 Classification of the literature

The following classification was used to systematically structure the particular literature.

A high number of papers were just taking into account the mitigation of collision risks in a very general way, if there was no connection to offshore wind structures like offshore wind farms and the use of AIS in a some way the papers were not used in this paper. Also papers which were not using AIS were discarded for the sample. Some nevertheless useful publications which did not made the cut are still noteworthy and are mentioned here.

(Xiao et al. 2022) give a very good overview as they compare models for the risk assessment of vessels with structures in a general way. They however do not concentrate on offshore wind turbines and thus are here just mentioned for reference. (Kao et al. 2021) also published a general model to prevent collisions using a fuzzy logic approach. (Mujeeb-Ahmed et al. 2018) were conducting a probabilistic approach to collision risks with offshore platforms. Since they were looking at oil and gas platform the paper will not be discussed into detail in this review in detail but the findings can be used to transfer findings to offshore wind farm collision risks.

The topic of this paper is not widely discussed in the scientific community at this point. But seeing the increase in the use of large data sets by machine learning approaches, simulation or other means like neural networks because of more relevant data and also more powerful information technology this topics will increase in use over the next years.

In the reviewed papers the following six groups were identified and the papers were structured into these groups:

- Mathematical Models / Numerical Models
- Detection / Near Miss / Prediction Models
- General Models / Risk Assessment Models
- Simulation Models
- Machine Learning / Deep Learning Models

- Trajectory Models

Table 3 shows this in a structured way.

Table 3: Classification of the literature (Own representation)

Authors	Mathe-matical	Detection	General	Simu-lation	Machine Learning	Trajec-tory
(Borkowski 2017)						**X**
(Chang et al. 2014)			X			
(Copping et al. 2016)	X					
(Lv et al. 2021)	X					
(Ma et al. 2022)				X		
(Mehdi et al. 2020)						**X**
(Mou et al. 2010)		X				

Authors	Mathe-matical	Detection	General	Simu-lation	Machine Learning	Trajec-tory
(Murray and Perera 2021)					X	
(Naus et al. 2021)			X			
(Park et al. 2021)					X	
(Rawson and Brito 2022)			X			
(Rawson and Rogers 2015)		X				
(Suzuki et al. 2013)	X					
(Scheidweiler and Jahn 2019)			X			

Authors	Mathe-matical	Detection	General	Simu-lation	Machine Learning	Trajec-tory
(Tabi Fouda et al. 2019)		X				
(Tranberg et al. 2019)					X	
(Tsai and Lin 2021)			X			
(Wawruch and Stupak 2011)			X			
(Yoo and Jeong 2017)			X			
(Yu et al. 2020a)						**X**
(Yu et al. 2020b)			X			
(Zhang et al. 2015)		X				

Authors	Mathe-matical	Detection	General	Simu-lation	Machine Learning	Trajec-tory
(Zhang et al. 2016)	X					
(Zhang et al. 2018)						**X**

4 Findings

The following paragraphs will show the findings after the mentioned papers were thoroughly examined.

4.1 Mathematical Models / Numerical Models

The following chapter shows the use of mathematical or numerical models for the AIS models. Four papers have this as a focus.

(Copping et al. 2016) did a numerical model using AIS-data as input for a simulation typical movements of e.g. cargo ships, tanker, etc. along typical used sea lanes of the Atlantic coast of the United States. The authors are only concerned with the long term effects of navigational safety during the operation phase of an offshore wind farm. They took AIS-data from 2010-2012 and filtered to one minutes intervals and thus vessel tracks were generated which were used as input into the numerical model to determine the likelihood of the accident between a commercial vessel and an offshore wind farm off the Atlantic coast of the United States (Copping et al. 2016). In contrast to similar studies for Europe there is no before / after effect observable in real live because there are not commercial offshore wind farm projects of the Atlantic coast of the US compared to projects in the German or British North Sea. (Copping et al. 2016) model shows after the run of 17 simulation that there is no “statistically significant increase in the mean frequency of collisions for the wind farm scenario […]” (Copping et al. 2016).

(Zhang et al. 2016) proposed an advanced method for the detection of near miss ship collisions using AIS-Data by developing a mathematical model. They develop a conceptual framework whereas they use the AIS data to determine the spatial characteristics of the traffic in a particular area. They calculate a “Vessel Conflict Ranking Operator (VCRO) to evaluate how grave a navigation conflict is by determining the safety distance between ships incorporating AIS data, ship size and the ship domain.

(Suzuki et al. 2013) were formulating a mathematical model with deals with the impact of an accidentally drifting vessel into an offshore wind farm.

(Lv et al. 2021) use a Fuzzy Inference System to conduct a navigational risk assessment for offshore wind farms. “By extracting visibility, the number of traffic flows, the number of meeting areas, and distance between sailing routes and wind farms, the risk of natural condition and navigational environment operation in the navigational system of ships in the wind farm area is, respectively, evaluated.”

It can be seen that mathematical models are used in a very theoretical way and the value to apply these models to real life has to be considered. The use of a mathematical model is quite static and it is to be valued if these models give a valuable answer to the problem that there are multi dependent inputs into these models.

4.2 Detection / Near Miss / Prediction Models

The following chapter deals with the findings of publications which deal with the detection and prediction of vessel behavior by analyzing AIS-Data. The analysis of near misses is also in this category.

(Rawson and Rogers 2015) did a study to assess the impacts to vessel traffic from offshore wind farms in the Thames Estuary by using a predictive analysis. They looked at five windfarms of the coast of the UK in the Thames estuary and the vessel movements recorded using AIS before the windfarms were build and after the windfarms were build. These datasets were then analyzed and presented in a Geographic Information System (GIS) (Rawson and Rogers 2015). The shortcomings of the study were that (Rawson and Rogers 2015) only focused on ships passing by the windfarms and vessels which were involved in construction or the Operation and Maintenance of the offshore windfarms were discarded. Additionally no fishing vessels or sailing boats were taking into account (Rawson and Rogers 2015).

(Tabi Fouda et al. 2019) developed a software model to control the movements of ships in an offshore area so that actions can be done before accidents happen and to visualize this using a GIS.

(Mou et al. 2010) uses the aforementioned SAMSON model to analyze AIS-data in linear regression model for the area around the busiest port in Europe, the port of Rotterdam. They used a timeframe of 62 days in Sommer of 2007. The port of Rotterdam was chosen because the AIS-data for this area is available and the model can be easily transferred to other busy area with a high traffic density. The study also revealed that in that part of the North Sea tankers have the highest risk profile for a collision (Mou et al. 2010).

(Zhang et al. 2015) developed the “Vessel Conflict Ranking Operator” which is a new method to detect near miss ship-ship collision and was used on data from the Northern Baltic Sea.

The strength of the aforementioned models is that they use real AIS-data and take into account the multiple influences of the behavior of vessels in or near offshore wind farms and thus try to predict possible accidents before they happen and to mitigate the risks of these accidents to happen. It is also useful that (Rogers et al. 2015) and (Mou et al. 2010) did their studies in areas where there will be a lot of offshore wind activity, like the Thames Estuary were a lot of offshore wind farms are already been built and even more will be built in the future or the approach to the port of Rotterdam which is the port in Europe with the most traffic.

4.3 General Models / Risk Assessment Models

(Rawson and Brito 2022) did a study to assess the validity of navigational risks assessments for the United Kingdom. In this study they compared the made predictions to the real historic incident record in regard to offshore wind farms in British Waters. Nevertheless they state that: “[…] it is difficult to access the validity of the underlying models and their applicability to OWFs given the sparsity of historical accident data” (Rawson and Brito 2022). Because there is not particular database of accidents in particular regard to only accidents with offshore wind farms (Rawson and Brito 2022) did review five general British accident databases and used additionally secondary resources for the years 2010-2019. In total they identified six collisions between vessels, 29 incidents involving a vessel and a fixed offshore structure (e.g. offshore wind turbine or substation), as well as 21 groundings and 13 near misses for a total of 69 incidents (Rawson and Brito 2022). Of these incidents interestingly 36% were occurring within the wind farm and 20% outside of the windfarm. The rest was happening within O&M ports. (Rawson and Brito 2022). Additional noteworthy is that 82% percent of the involved vessels are vessels working in the particular offshore wind farm (e.g. Crew Transfer Vessels (CTV) and Offshore Supply Vessels) and just the rest of 18% were commercial vessels or leisure vessels. The split of incidents between the construction phase and operational phase is 50%:50% thus leading to the conclusion that the shorter construction phase is much more prone to collision incidents. (Rawson and Brito 2022).

(Naus et al. 2021) did a study as a posteriori vessel traffic analysis for offshore wind farms in Polish waters using historical AIS-data. The study showed that the "research results confirm the hypothesis that it is possible to use historical AIS data during the implantation of the spatial planning process aimed at optimizing the location of marine renewable energy installations." (Naus et al. 2021).

(Chang et al. 2014) were assessing the navigational risks of the development of Offshore Wind Farms off the coast of Taiwan using AIS-data. Chang et al. used this data among others research questions to estimate the frequency of possible collisions between ships and an offshore wind farm.

(Wawruch and Stupak 2011) show in their paper which input of AIS-data is necessary for an analysis and then they discuss current used collision models by research institutions and private companies and compare these models by calculating the probability of a collision between a ship and a wind farm.

(Yoo and Jeong 2017) were doing a research study regarding the risks offshore wind farms pose for fishing vessels and vice versa. They conclude that September is the riskiest month and that there should be a least a safety zone of 0.3 NM around offshore wind farms to mitigate the collision risks for fishing vessels with offshore wind structures (Yoo and Jeong 2017).

(Yu et al. 2020b) conducted an assessment of the “Influence of offshore wind farms on ship traffic flow based on AIS data”. Here they used AIS data of two years with 26,645 ships in a particular area in Chinese Waters in 2014 before the wind farm was built and this number was reduced to 17,444 vessels after the wind farm was built meaning that a high number of vessels had to change their trajectories because of the new situation. (Yu et al. 2020b)

(Tsai and Lin 2021) used AIS-data to improve the navigational safety in regard to offshore wind farms in the Taiwan Strait. There were also looking at the impact of fishing vessels and especially at the bottlenecks in the shipping lanes created by the development of offshore wind farms (Tsai and Lin 2021).

It is not a surprise that there are a lot of general models / Risk Assessment models in the literature since before an offshore wind farm can be built a navigational risk assessment has be done. Since these risk assessments are in general done by commercial companies these are normally not of a scientific nature like the aforementioned publications. Nevertheless these approach is of interest for researchers too, and since it is not that particular complicated to analyze historical AIS-data the publications above did exactly that. This approach is very useful but should be combined with further methods to return more robust results.

4.4 Simulation Models

(Ma et al. 2022) papers takes into account a evaluation of the risk of a vessel to collide with a structure (the Jiantian Bridge in China) by combining AIS-data and Bayesian Networks in a Monte Carlo Simulation. Even though this model is not geared at offshore wind structures the authors of this paper believe that it can be transferred to be used for other offshore structures like offshore wind turbines or offshore substation as well.

Rather surprising is that there is only one publication which explicitly uses simulation to determine the collisions risks using AIS-data and Bayesian networks between offshore structures (in this case a bridge) and vessels. Even though the number of publications is insufficient for this group it can be assumed that in the future more publications with the use of AIS data in a simulation will be published.

4.5 Machine Learning / Deep Learning Models

(Park et al. 2021) developed a model to predict the trajectory of vessels using a machine learning based approach using collected AIS-Data of 14 days in the waters close to South Koreas biggest port, Busan. The dataset included 1351 vessels and 2816 trajectories and was divided into four types of vessels: cargo, passenger, oil tanker and dangerous cargo ship.

(Murray and Perera 2021) developed a deep learning framework for the prediction of ship behavior based on historical AIS-data. The investigated area will be divided into clusters and each cluster contains trajectories with similar behavior characteristics. In each of these clusters a local model will be generated to describe the local behavior in the cluster. The authors propose to: "[…] to cluster historical trajectories using a variational recurrent autoencoder and the Hierarchical Density-Based Spatial Clustering of Applications with Noise Algorithm." (Murray and Perera 2021). (Scheidweiler and Jahn 2019) did a paper on the use of AIS data in business analytics and their potentials and limits. They show what potential uses and opportunities can be achieved by using AIS-data in machine learning approaches.

(Tranberg et al. 2019) used k-means clustering, an Machine Learning approach to identify the time and processes of offshore installation processes using AIS-data. Even though (Tranberg et al. 2019) did not use their model specifically to determine or mitigate the collision risks of offshore wind farm projects the authors of this paper are confident that the model by (Tranberg et al. 2019) could be also used for this research question.

Machine Learning models are very useful for the prediction of collisions of vessels with offshore wind farms. Since there is a lot of data generated by AIS, machine learning algorithms can be useful employed to filter, clean, group and analyze the large amounts of data to determine patters and thus help to generate models to for prediction of collision risks and to mitigate these risks. Since over time even more AIS data will be created and computer power is also increasing the robustness of these models will also increase.

4.6 Trajectory Models

(Zhang et al. 2018) suggest a "[…] multi-regime vessel trajectory reconstruction model through three-steps processing, including (i) outliers removal, (ii) ship navigational state estimation and (iii) vessel trajectory fitting". The AIS-dataset consisted of 500 ships which used the port of Singapore. (Zhang et al. 2018) state that their model can decrease the errors like abnormal rate of speed (from 43,42% to 0.00%), acceleration (from 10.65% to 0.00%), ROT (Rate of Turn) (from 50.33% to 15.81%) and jerk (from 59.25% to 17.82%) and is thus much better than other models , e.g. linear regression models, polynomial regression model or the weighted regression model.

(Mehdi et al. 2020) developed a deterministic method which can either be used operational by seafarers or strategically in the planning stages of an offshore wind farm project by the project developers.

(Borkowski 2017) e.g. proposed a trajectory prediction model which used several neural networks which were learning from maritime data.

(Yu et al. 2020a) use a semi-qualitative risk model using Bayesian networks to do the risk assessment of ship flows close to offshore wind farms. Here the Bayesian network is trained on available AIS data sets so it is able to describe actual traffic flows. Then the authors use expert opinions using evidential reasoning to identify the most important risk factors.

Trajectory models are another approach. These models seem also to be very useful in analyzing historical data and training to predict the behavior of vessels near or in offshore wind farms. Here the researchers looked mainly at the real traffic flows and the trajectory of the vessels to determine the environment and the movements of the vessels and based on that they determine not normal behavior to access the risk of a collision.

5 Conclusions

This overview can only show the current state of research and is also very focused on a narrow part, the analysis of mitigating collision of vessels with offshore wind structures by using AIS data. Currently mathematical models are used to a high degree but since these are very theoretical and do not take into account the multi interdependency of inputs into the collision models between vessels and offshore wind farms it can be assumed that the use of these models will decline in the future.

Surprisingly traditional simulation approaches are only used to a small degree.

Risk assessment models using historical AIS data are very widely used and are definitely useful in the analysis of collision risks. Additionally they are relatively easily to conduct. The same holds true for trajectory models.

However the authors determine that the biggest improvement will be the greater use of machine learning models to determine the collision risks between vessels and offshore wind farms.

The use of machine learning models will likely increase in the future because the conclusions drawn from these models will be more thorough and useful than from other methods. There is a high amount of AIS-data generated and by using the appropriate algorithms machine learning will be very useful in predicting collisions of vessels with offshore wind farms.

The topic of this paper will definitely become more important over the next years because there will be more projects in the North Sea but also off the Atlantic Coast in the USA and in China. All this three areas are heavily traversed by commercial shipping and will also likely see even more vessel movements over the next years.

There are a lot of research questions still open and answers to these can be given by developing novel and innovative approaches. Especially the advances in handling of large datasets by new approaches using machine learning will lead to improvements in this area.

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