Improving maritime safety at the North Sea by anomaly detection

Master of Science Thesis

Hydraulic Engineering

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by

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to obtain the degree of Master of Science
at the Delft University of Technology,
to be defended publicly on November 21, 2024

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Acknowledgment

This thesis represents the final step of an exciting and challenging journey, and I couldn't have done it without the support of others. It has been written as part of the requirements for the Master of Science degree in Civil Engineering, specializing in Hydraulic Engineering, at Delft University of Technology. This research was conducted at Witteveen+Bos as part of a graduate internship.

A year and a half ago, I wasn't sure if I would graduate, but I'm glad I pushed through (with help). The project work suited me better than the courses did. I was fortunate to be supervised again by Fedor and Solange, who had also guided me during an earlier internship. At the time, Artificial Intelligence was becoming unavoidable, and although I knew little about it, it sparked my interest and offered a lot to learn. I also wanted to gain experience working with a company, which led me to Witteveen+Bos, where a similar project on nautical safety had just been completed under the same supervision.

I am grateful to my committee for their guidance and support throughout the process. First of all, I would like to thank Solange for her guidance and for pushing me to keep moving forward. I am thankful for her taking me to the symposium, helping to organize a workshop, and accompanying me to the Coast Guard Center. It was a great opportunity to learn more about the field and meet other people.

I would also like to thank my internship supervisor at Witteveen+Bos, Lex, for his perspective and the valuable tips he provided throughout the project. Additionally, I want to express my gratitude to Fedor for the knowledge he shared on programming and more.

Patricia helped keep me sharp in explaining the choices of my methods and the clarifications in my report. Finally, I would like to thank Mark for providing valuable insights into the broader scope of the research and its framing.

Many thanks to Coast Guard, RWS, MARIN, and Deltares for their valuable contributions to the workshop, and a special thank you to the Coast Guard for allowing a visit to Den Helder.

Gratitude goes to the colleagues at Witteveen+Bos for making me feel welcome. I would like to thank the fellow students in the graduation room 3.95 for the enjoyable atmosphere and the helpful feedback.

Deep thanks to my friends and family for their unwavering support and for helping me through the challenges along the way.

Finally, I want to express my gratitude to everyone who's played a part in this journey. Whether big or small, your support has been truly appreciated and has made all the difference.

Jessica van den Heuvel
Delft, November 2024

Abstract

Following the Paris Climate Agreement, the Dutch government established a target of at least 55% reduction in CO_2 emissions by 2030. This target will be achieved through the development of wind farm areas in the Dutch part of the North Sea, capable of generating 10.7 GW of wind energy. The construction of offshore wind farms, alongside the occupation of areas in the North Sea for other purposes and developments in shipping, reduces the available space for shipping. This reduction limits room to maneuver and increases the likelihood for incidents. This was also highlighted after Onderzoeksraad Voor Veiligheid (2024) published a report following the incident with the Julietta D. in January 2022. This bulk carrier drifted and collided with an oil tanker, a windfarm transition section and a platform under construction at a wind farm, after 13 minutes, 49 minutes and 4 hours and 6 minutes respectively. The report emphasized that building wind farms close to shipping lanes leads to a deterioration in maritime safety. Meanwhile, the Dutch Coast Guard provides assistance and services for the Dutch part of the North Sea by constantly monitoring maritime traffic. This is done through screens and communication tools, with just five people, including three operators. As a result of the Coast Guard's current operational setting, combined with the aforementioned developments in the North Sea, the Coast Guard may realize too late that a dangerous situation is developing, delaying their ability to respond.

Several studies showed rule-based approaches for monitoring of maritime traffic for safety and security purposes, and Machine Learning-based approaches for anomaly detection in Automatic Identification System (AIS) data. Other studies used alternative sources in addition to AIS data. The rule-based approaches are limited to known behaviour and require periodic updates. The Machine Learning-based approaches do not seem to adequately consider environmental conditions. The objective of this research is to contribute to the North Sea safety monitoring of Coast Guard operators by developing a Machine Learning-based model in other words, a non-rule based approach. This model can detect vessels showing anomalous behaviour in AIS data, taking into account the detection speed. The operators can be assisted by visually highlighting ships that exhibit anomalous behaviour. In this research, anomalous behaviour is interpreted as behaviour deviating from generally shown behaviour taking into account ship motion and factors influencing sailing behaviour. This research is primarily based on AIS data of cargo ships from the the North Sea. It concentrates on the safety aspect (not security) of monitoring tasks. The research question was stated as follows: 'How can machine learning enable operators to detect anomalous cargo vessel behaviour with potential safety implications, on the North Sea, more quickly, validated against historical data from a known incident'.

Safety concerning behaviour is considered from two perspectives: casualty events and behaviour patterns. A framework is used to classify different types of anomalous behaviour, namely anchorage outside the port, drifting, spoofing position, entering an area of interest, sudden change of heading, heading approach to or off shore, ship/ activity at port at sea, ship encounters, not reporting, ship in area at certain time of the day, sudden change of speed and distance to shore. The behaviour pattern drifting, linked to loss-of-control as a casualty event, is used to validate the model. Contributing factors to sailing behaviour are listed and a selection for the behaviour type drifting, are implemented in the model as features.

A model for anomaly detection is developed, utilizing a machine learning approach and techniques, following a literature review. Using AIS data logs of vessels, trajectories are generated and segmented into trips based on a predefined duration, with a start time for splitting. Behaviour and contributing factors to behaviour, are described using features extracted from these trips, either individually or in combination with the spatial arrangement of the North Sea (as spatial properties) and metocean conditions. Based on the trips and their distinctive features, represented as points, a two-dimensional embedding was generated using the dimension reduction technique densMAP. This technique, a density-preserving visualization tool based on Uniform Manifold Approximation and Projection (UMAP), preserves both local and global structure in the embedding. Trips with similar features are plotted close to each other in the embedding. The Local Outlier Factor (LOF) is applied to detect local outliers, based

on local densities, in the embedding. Through outlier detection, trips exhibiting anomalous behaviour were identified. The LOF technique was applied to detect local outliers based on local densities in the embedding. The contamination factor as well as the number of neighbors, can be adjusted in the algorithm, depending on the number of trips and distances between points.

The validity of the detection model and the speed of the detection is shown using the case study on the drifting incident involving the bulk carrier Julietta D.. AIS data from cargo ships, covering the two days (January 31st and February 1st) and the area in the North Sea where the Julietta D. drifted in 2022, were used. Different combinations of features, trip durations (30 and 60 min) and model settings (contamination factor) were tested to check the speed and accuracy of the outlier detection. Results show that the Julietta D. can successfully be detected in 30 minutes. Features used to describe the ship's motion are length to beam ratio and the mean, standard deviation, maximum, minimum, 10% quantile, median, 90% quantile and skewness of the Speed Over Ground (SOG) and Rate Of Turn (ROT). Features used to describe the spatial properties of the trip include whether the trajectory was present in the anchorage area, in the approach area, in the safety zone of the wind park and if it crosses the Traffic Separation Scheme (TSS). For the metocean conditions, features are used for velu, velv, swh, mwd, u10 and v10, which represent the eastward- and northward component of the velocity, the significant wave height of combined wind waves and swell, mean wave direction and eastward- and westward component of the wind speed at 10 meters above the surface respectively. The contamination factor was set on 1% and the number of neighbors is 20. In addition to detecting the Julietta D., different groups of points, or clusters, were plotted as trajectories and the feature importance was visualized. Furthermore, by plotting groups, an estimation could be made of whether the model could detect other anomalou behaviour types. The model can detect drifting vessels, detect if the vessel is anchored outside the port, and if a vessel displays a sudden change of speed. Furthermore, the model has potential to detect if a vessel is present in a specified area, if a vessel displays sudden change of heading and if a vessel is present at a location at a certain time of the day. Other behaviour types are outside of the scope of this research.

A limitation of the research is that the heading information in the AIS data is not considered as (part of) a feature, due to its unreliability. In addition, the validity of the detection model is shown with a limited amount of AIS data over time and a single drifting incident. Additionally, the model does not account for global outliers and cannot identify different types of anomalous behaviour.

It can be concluded that machine learning based on anomaly detection has the potential to enable operators to identify anomalous cargo vessel behaviour, with potential safety implications on the North Sea, more quickly (within 30 minutes). Anomalous cargo vessel behaviour is operationalized by translating the detection speed into a measurable parameter. This is achieved by filtering for cargo vessels and by defining a start time and trip duration. Various specifications for the practical application of the detection model, concerning operator usage and application in an operational setting, were determined. The selected approach and methods for anomaly detection, using machine learning, were integrated into a workflow and are generally applicable and reproducible. The model is scalable by overlaying a grid on the North Sea, with each cell (or tile) having its own embedding and outliers. The model instills confidence by grouping trips exhibiting similar behaviour and is interpretable by displaying the features of these groups. Additionally, the model can be explained through interactive plotting of points, outliers or by manual selection in the embedding. These points are visualized as trajectories on the North Sea. The model is potentially useful for the Coast Guard in relation to analyses of unusual behaviour, training and supporting current operational detection. In terms of research relevance, a combination is established between the rule-based tasks performed by the operators and the creation of rules derived from data. This approach integrates practical experience with insights gained from data analysis.

The main recommendation for enhancing the model are to add a time component as a feature and to incorporate a global outlier detection method. Furthermore, it is recommended to utilize labeled dataset, enabling supervised machine learning, of known incidents to verify features in the detection method and to identify features associated with different types of anomalous behaviour. Finally, the model can be validated using publicly available AIS data of the United States.

In the field of monitoring maritime traffic using AIS data combined with machine learning techniques, there are still numerous opportunities for further exploration.

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Acronym

ABM Automated Behaviour Monitoring

AI Artificial Intelligence

AIS Automatic Identification System

API Application Programming Interface

COF Connectivity-based Outlier Factor

COG Course Over Ground

CRS Common Reporting Standard

DBSCAN Density-Based Spatial Clustering of Applications with Noise

DBSCANSD Density-Based Spatial Clustering of Applications with Noise considering Speed and Direction

DE-9IM Dimensionally Extended Nine-Intersection Model

EEZ Exclusive Economic Zone

EML Explainable Machine Learning

EMCIP European Marine Casualty Information Platform

EMSA European Maritime Safety Agency

EPSG European Petroleum Survey Group

ETA Estimated Time of Arrival

HDBSCAN Hierarchical Density-Based Spatial Clustering of Applications with Noise

IMO International Maritime Organization

KDE Kernal Density Estimation

LOF Local Outlier Factor

LoOP Local Outlier Probabilities

MIK-NL Maritiem Informatie Knooppunt

ML Machine Learning

MMSI Maritime Mobile Service Identity

MOSWOZ Monitorings- en Onderzoeksprogramma Scheepvaartveiligheid Wind op Zee

NaN Not A Number

NUC Not Under Command

PCA Principal Component Analysis

QGIS Quantum Geographic Information System

RF Random Forest

RMD Radio Medical Service

ROT Rate Of Turn

SAR Search And Rescue

SHAP SHapley Additive exPlanations

SOG Speed Over Ground

SOLAS International Convention for the Safety of Life at Sea

TREAD Traffic Route Extraction and Anomaly Detection

tsfresh Time Series FeatuRe Extraction on the basis of Scalable Hypothesis tests

t-SNE t-Stochastic Neighborhood Embedding

TSS Traffic Separation Scheme

UMAP Uniform Manifold Approximation and Projection

UTC Coordinated Universal Time

1
Introduction

It was the end of January 2022 with a strong gale with gusts of about 48 knots, very high waves and swell of six meters high. On this day, the cargo ship Julietta D. became adrift in the North Sea. The ship hit an oil tanker, resulting in a hole in the engine room. The captain and crew had to disembark, prompting a Coast Guard rescue. The ship then drifted into a wind farm. There it collided with a platform under construction, causing extensive damage (AD, 2022).

1.1. Cause and Context

The North Sea is one of the most intensively used seas in the world. The available space in this this area is used by nature reserves, fishery and offshore wind farms. The planned expansion of wind farms is expected to significantly reduce the shipping space. The government's target of at least 55 percent CO_2 reduction by 2030, resulting from the Climate Agreement of Paris, is realized by designating offshore wind energy areas, resulting in an additional 10.7 GW of wind energy until 2030 in the Netherlands.

Periodic analysis of shipping traffic in the North Sea show an increase in the number of ship movements (and gross tonnages transported). In addition, the size of ships is still increasing and the diversity in the composition of shipping traffic is increasing as well. A volume growth of 35 to 40 percent until the year 2030 is expected (Ministerie van Infrastructuur en Waterstaat et al., 2022).

Due to the construction of offshore wind farms and expected growth in ship movements, the traffic intensity and traffic dynamics of the North Sea will increase. The increased traffic in combination with the reduced available space, and additional objects (wind turbines) in the North Sea increases the probability of incidents.

A recent report of MARIN (2019) on the implication of wind farms, in the North Sea, for maritime safety expresses the expectation for 2030 that once every 10 years a large ship will collide with one or more wind turbines with major consequences. Wind farm construction increases the risk for shipping and for wind turbines, because of the large number of turbines located close to shipping routes with little room to divert.

Onderzoeksraad Voor Veiligheid (2024) published a report, following the Julietta D. incident, addressing the growing safety risks for shipping in the North Sea, arising from the increasing placement of wind turbines. The report highlights that, despite the implementation of certain measures, such as the maintenance of buffer zones between wind farms and shipping lanes, research revealed a potential deterioration in shipping safety due to the proximity of wind farms to traffic routes. In response, seven measures were introduced to address the identified risks. These include the establishment of traffic control, the installation of additional sensors around and within the wind farms, the provision of more emergency tugs, and the launch of Monitorings- en Onderzoeksprogramma Scheepvaartveiligheid Wind op Zee (MOSWOZ). The report ended with a recommendation that, in order to manage the risks to shipping safety in the North Sea both now and in the future, a different, integrated approach to risk management is needed, one that takes into account the ever-changing situation in the North

Sea, considering new developments in shipping and other activities in the North Sea.

1.2. Problem description and research gap

The Dutch Coast Guard provides assistance and services at the Dutch part of the North Sea and extensive inland waters (see Figure 1.1), where they take action in case of disasters and incidents. Maritime traffic in the North Sea is monitored using screens and communication tools. The moment an incident occurs, a report is made, which arrives at the Coast Guard Center, allowing for appropriate action to be taken. The Coast Guard Center is staffed 24/7 by a limited number of people, namely a Duty Officer, three Watch Officers (operators) and a colleague from enforcement services (see Figure 1.2) (Kustwacht, 2024). As a result of the Coast Guard's current operational setting and developments at the North Sea, the following challenges maintaining maritime safety could potentially arise:

- Human detection by operators in dangerous situations in the North Sea is challenging considering to the growth in the number of ships. The current safety system (VTS and VTMonitoring) does not (yet) automatically highlight or warn for potential risks of accidents throughout the North Sea.
- Less space available for navigation results in less room for errors and less time to intervene in unexpected situations. This requires a faster response of the captain and the Coast Guard Centre to avoid accidents or limit their consequences.
- When there is less time to intervene, the captain is more likely to use the available time to focus on controlling the ship rather than reporting the current situation to the Coast Guard Centre. As a result, the awareness of potential risks for an incident comes to the Coast Guard's attention later, which could potentially result in a delay in assistance and/ or intervention.

The Coast Guard may realize too late whether a dangerous situation is developing, delaying their ability to response. Marine Safety Investigation Unit (2023) conducted an investigation into the incident with the Bulk Carrier Julietta D., which revealed that between the moment the ship reported to be dragging its anchor and the moment the ship made contact with the wind farm transition section under construction, in the wind farm area, was around 47 minutes. The time between the ship being Not Under Command (NUC) and hitting the oil tanker was around 13 minutes.

Liao et al. (2021) developed a simulation platform for an airport runway collision warning system. This system utilized real geographic coordinate data from airport maps to generate a dynamic on-board moving map for the pilot to define several kinds of runway intrusion scenarios. Idiri & Napoli (2012) proposed a system for the automatic identification of maritime accident risk. This system consists of the automatic acquisition of expert knowledge through automated exploration of historical maritime data and a rule-based reasoning mechanism. Iphar et al. (2020) proposed a method for the risk assessment of cyberthreats in maritime transportation data. Discovered abnormal reporting cases were assessed using an expert-designed, rule-based analysis framework. This assessment resulted in the activation of alerts and the assignment of risk levels, to raise the awareness of the people in charge of monitoring the maritime traffic. Simulation results of Gorkem et al. (2023) showed that rule-based approach is successful in detecting dark activities, which are vessels conducting operations discreetly or evade observation, but this approach tends to produce false alarms. In addition, the results showed that Machine Learning-based approach provides better overall accuracy. Karimi et al. (2024) described rule-based systems as systems using pre-defined rules to make decisions about content and feedback. Zaman et al. (2024) applied a Machine Learning-based approach for anomaly detection in Automatic Identification System (AIS) data, utilizing a passage plan or an extracted reference route.Seong et al. (2023) applied a Machine Learning-based approach for detecting abnormal ship movements using CCTV videos. Some Machine Learning approaches were used to detect incorrect AIS data (Szarmach & Czarnowski, 2022) or detect damagedAIS data that requires reconstruction (Szarmach & Czarnowski, 2024). Finally, B. Rhodes et al. (2006) presents SeeCoast, a port surveillance system developed for the US Coast Guard, providing scene understanding support for wathstanders. This system leverages various data sources to automatically detect pre-defined vessel activities, namely unsafe, illegal and threatening activities, using a rule-based pattern recognizer and detects anomalous activities with automatically learned behavior normalcy models. The data consists of streaming video data, radar and AIS data.

Several studies showed rule-based monitoring for maritime traffic safety and machine learning-based approaches for detection. Rule-based systems detect vessels based on predefined rules derived from known behaviors. Rules are typically customized for each location and require periodic updates to remain effective. The environmental conditions, which can significantly influence sailing behaviour, are not adequately considered in the machine learning-based detection approaches and none of these studies specifically focus on providing monitoring support for Coast Guard operators. However, B. Rhodes et al. (2006) employs both rule-based and machine learning approaches to assist the Coast Guard, but it is unknown whether SeeCoast takes into account environmental conditions.

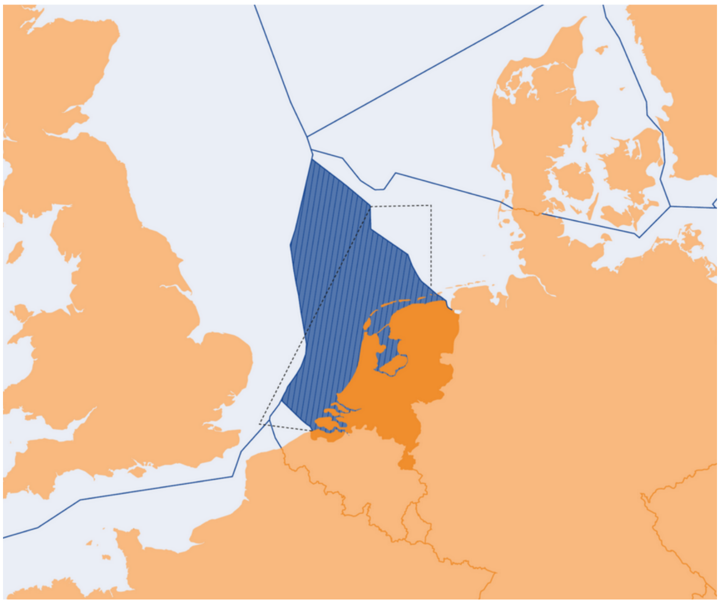

Figure 1.1: Area under the Coast Guard's responsibility for search- and rescue operations

Source: Kustwacht (2024)

Figure 1.2: Operational setting at the Coast Guard Centre

Source: Kustwacht (2024)

1.3. Research objective and scope

The objective of this research is to contribute to the North Sea safety monitoring of Coast Guard operators by developing a machine learning-based model, in other words non-rule based approach, that can detect vessels showing anomalous behaviour in AIS data. Anomalous behaviour can be approached in various ways. Lane et al. (2010) outlines five anomalous ship behaviours:

- Deviation from standard routes;
- Unexpected AIS activity;

- Unexpected port arrival;
- Close approach anomalies;
- Zone entry anomalies: vessels entering a restricted area.

Tu et al. (2018) classified ship anomalies into three types based on kinematic perspective:

- Position anomalies: ship appear in an unexpected location;
- Speed anomaly: ship shows unexpected speed;
- Time anomaly: the visiting time of a ship is unexpected.

In this research, anomalous vessel behaviour is interpreted as behaviour deviating from generally shown behaviour, with similar environmental conditions. The scope of this research consists of maritime traffic on the Dutch part of the North sea. AIS data is chosen as the primary data source for the project, which has been made available to the TU Delft for research purposes. Mainly using AIS data implies that ships not using AIS systems are excluded from this research. Cargo ships are of interest for this research, because these vessels are most commonly involved in marine casualties and incidents. This is shown in Figure 1.3 from the European Marine Casualty Information Platform (EMCIP) which stores and analyses data on marine casualties and incidents in Europe. European Maritime Safety Agency (2023) divides cargo ships into solid cargo and liquid cargo. Solid cargo consists of: barge, bulk carrier, container ship, general cargo, refrigerated cargo, RoRo cargo, heavy load carrier, pontoon and other. Liquid cargo is divided into chemical tanker, combination carrier, liquefied gas tanker (LNG and LPG), oil tanker (crude oil and product carrier) and tanker (liquid non-flammable). These vessels navigate over traffic separation schemes (route-bound traffic) and generally exhibit relative similar behaviour .

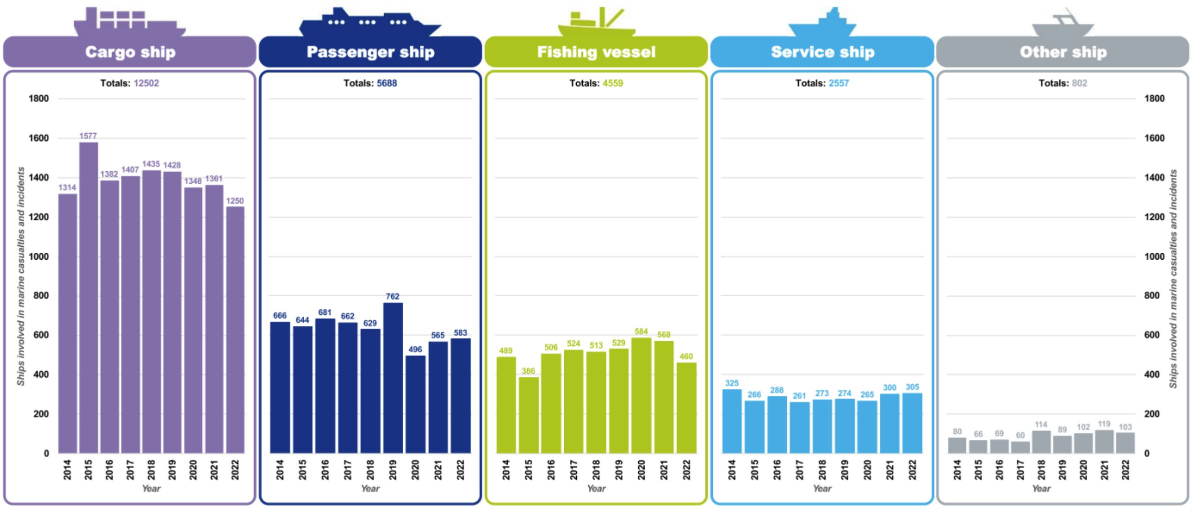

Figure 1.3: Number of marine casualties and incidents per ship type and per year

Source: European Maritime Safety Agency (2023)

1.4. Research questions

To achieve the stated research objective, a research question is defined:

> **”How can machine learning enable operators to detect anomalous cargo vessel behaviour with potential safety implications, on the North Sea, more quickly, validated against historical data from a known incident?”**

The research question is divided into the following sub-questions:

1. ”How are incidents and anomalous ship behaviour types currently regarded, how does the Coast Guard focus on these safety concerning behaviours, and what requirements should a detection model meet to enhance monitoring in the operational setting?”
2. ”What are contributing factors to safety concerning behaviour, and what anomalous behaviour should be detected?”
3. ”Which machine learning approaches and methods have a great potential to enhance operational tools for detecting anomalies?”
4. ”How can the geospatial-temporal behaviour of a ship, along with its contributing behavioral factors, be integrated into a model utilizing the selected machine learning approach and methods to effectively detect anomalies?”
5. ”Can the selected anomalous behaviour be detected by the model, what is the detection speed, and does the model have the potential to detect other types of anomalous behaviour?”

The research approach section provides more detail on how to answer the research- and sub-questions.

1.5. Report structure

The first step is to determine what types of behaviour and incidents are known in maritime traffic. This can be found in Chapter 2 Maritime Traffic. This chapter explains how the Coast Guard currently recognizes ships of interest in an operational setting based on a visit to the Coast Guard Centre and what are specifications for the detection model (Sub-question 1). Subsequently, AIS data is explained and characteristics of vessel behaviour are discussed. Finally, a decision is made as to what behaviour type the model should detect (Sub-question 2). In Chapter 3 Literature Review, the methods available for detection of anomalous behaviour are discussed by means of literature review (Sub-question 3). This chapter addresses machine learning approaches, methods for anomaly detection and anomaly detection in AIS data. The materials and methods for the detection model are elaborated in Chapter 4. The methods describe the different steps in the model to get from AIS data to detection of anomalous behaviour (Sub-question 4). Subsequently, the model is applied to a case study and results are generated (see Chapter 5 Results). The conclusions and discussion in Chapter 6 discuss the key findings and importance of the results, among others (Sub-question 5). Figure 1.4 shows the project’s approach and related chapters.

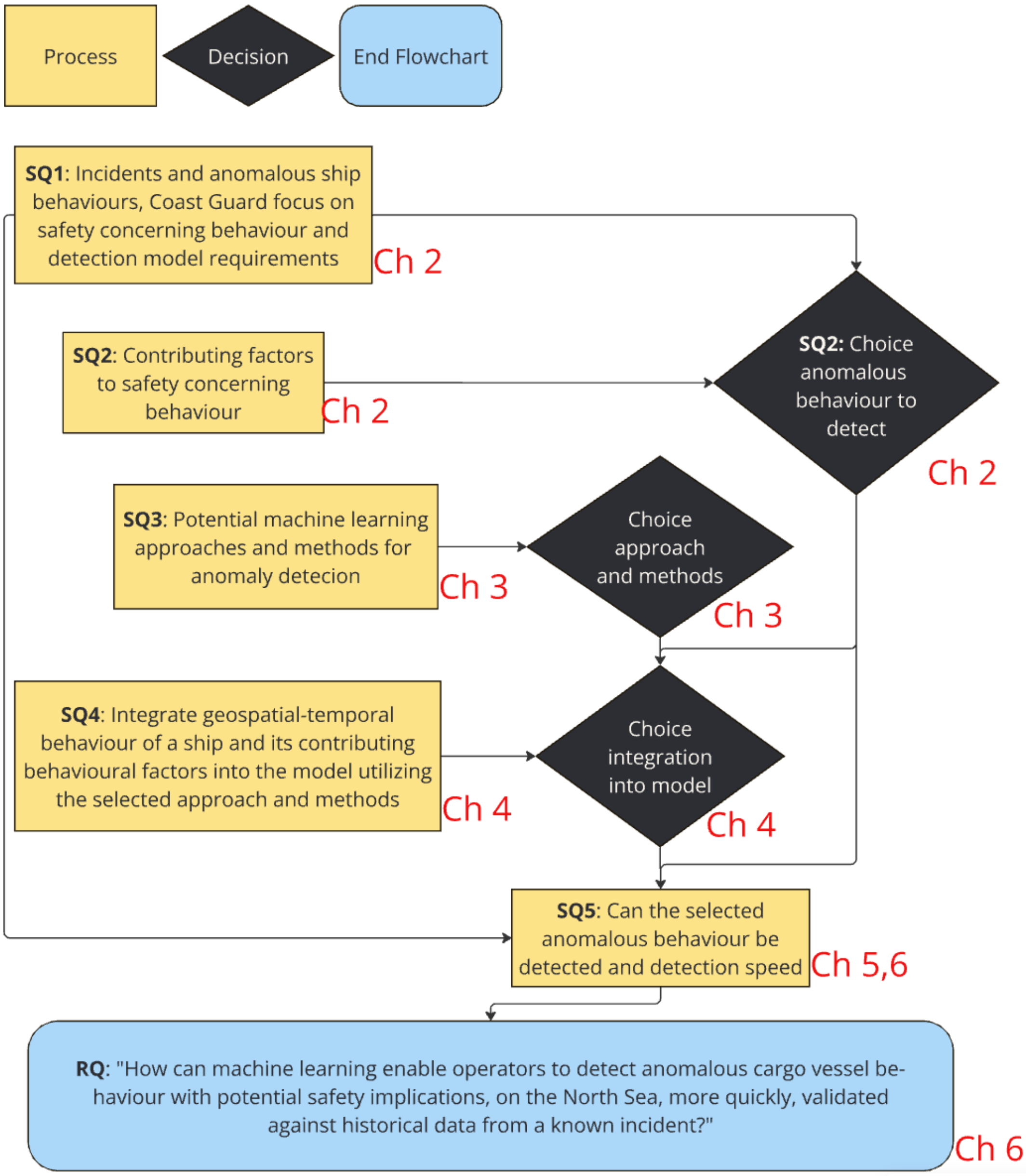

Figure 1.4: Flowchart of research questions and corresponding chapters

2
Maritime Safety

The introduction touched on an expected increase in traffic intensity and traffic dynamics on the North Sea. This raises the questions, what kind of incidents can these ship movements lead to and how can the nautical safety be improved by the Coast Guard? After answering these questions, this chapter will further discuss AIS data, classification of abnormal shipping behaviour, what anomalous behaviour will be detected, and a summary of the findings is given towards the end.

2.1. Nautical safety

According to Witteveen+Bos Raadgevende ingenieurs B.V. & Hofmeijer (2020), nautical safety concerns the extent to which the risks of maritime accidents are controlled to an acceptable and preferably negligible level. A maritime accident is described as an incident on water in which unintentional damage occurs and in which at least one vessel (sailing or stationary) is involved. Damage entails casualties, damage to one or more vessels involved, damage to infrastructure, damage to objects, environmental damage, complete blockage of a waterway, residual damage (such as loss of time, damage to household effects/ household goods and other damage). Insight into development of nautical safety is provided by Monitor Nautical Safety. The Ship Accident System (SOS-database) provides insight into the number of shipping accidents on the Dutch part of the North Sea, among others. For each shipping accident, the database provides information on the location, date and time of the accident and usually information on the circumstances, possible cause and effects of the accident.

2.1.1. Safety concerning behaviour: casualty events and behaviour patterns

In addition to a national database, an international database also exists, namely the European Marine Casualty Information Platform (EMCIP). European Maritime Safety Agency (EMSA) publishes annual overviews of Marine Casualties and Incidents, which analyses marine casualties and incidents reported by the EU Member States in the EMCIP. A codification of information on marine accidents was prepared by EMSA, describing several elements that link the consequences of an accident to its root events (see Figure C.1). The contributing factors to accidental events and subsequently casualty events is elaborated in the section on ship behaviour.

European Maritime Safety Agency (2023) describes an accidental event or accident event as, ”an event that is assessed to be inappropriate and significant in the sequence of events that led to the marine casualty or incident”. The casualty event is described as, ”an unwanted event in which there was some kind of energy release with impact on people and/or ship including its equipment and its cargo or environment”. A casualty event involving one or more ships can be classified in capsizing/ listing, collision, contact, damage to or loss of equipment, grounding/stranding, fire/explosion, flooding / foundering, hull failure, loss of control, missing, and non-accidental events (see Figure C.1).

Next to casualty events, European Maritime Safety Agency (2024) made a distinction in behaviour patterns for Automated Behaviour Monitoring (ABM) (see Figure 2.1). The behaviour patterns consists of anchorage outside the port, drifting, spoofing position, entering an area of interest, sudden change b

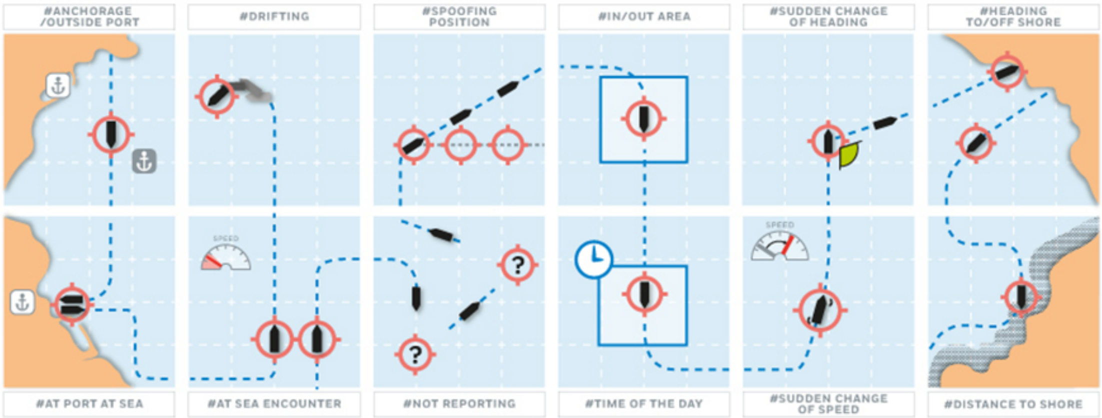

Figure 2.1: Detection specific or anomalous ship behaviour patterns

Source: European Maritime Safety Agency (2024)

of heading, heading approach to or off shore, ship/ activity at port at sea, ship encounters, not reporting, ship in area at certain time of the day, sudden change of speed and distance to shore. Spoofing is the deliberate manipulation of an AIS device to hide or alter a vessel's location or identity. The mentioned casualty events and behaviour patters are known behaviours and can be used for rule-based detection. The behavioural patterns of EMSA are used to define behaviours for this research (see Figure C.1).

2.1.2. Operational setting Dutch Coast Guard

The Coast Guard is responsible for the following three main tasks:

- Aid and services
- Enforcement
- Maritime Security

The former task, aid and services, is related to this research. Aid and services is subdivided into Search And Rescue (SAR), disaster- and incident response, explosives clearance, nautical management, Radio Medical Service (RMD), fairway marking and traffic control. There are different demarcations of areas of work, such as SAR, surveying and airspace. The search and rescue operations cover the Dutch EEZ, Wadden Sea, Ijsselmeer, Randmeren, Zuid-Hollandse stromen and Zeeuwse stromen.

To get a better understanding of the operational setting of the Coast Guard, a visit was made to the Coast Guard center in Den Helder (see Appendix A). The Coast Guard brings together different sources of information to obtain a clear picture and assess the situation on the Dutch part of the North sea. Monitoring tasks are based on information from two main sources:

- Through screens and communication tools. The screens show current ship positions, and if necessary, a certain history (trajectory, origin) can be retrieved. This also makes extensive use of public sources such as Marine Traffic. The operators monitor themselves, based on current positions, whether a ship shows anomalous behaviour (e.g. stopping somewhere for an unusual long time or sailing over a pipeline). In addition, based on reports, situations or ships come into focus (e.g. from shippers in distress).
- Through intelligence Cases come to light within the Maritiem Informatie Knooppunt (MIK-NL), where various authorities (i.a. police, customs, royal navy) physically sit together to exchange information.

If remarkable information arises, contact can be made with the skipper, for example, or the Coast Guard can ask for an aircraft to inspect the relevant location. In addition to experience, context plays an important role in assessing and determining whether shipping behaviour is deviant or explainable (e.g. some ships have permits to cross certain areas). How quickly anomalous behaviour is noticed depends on the situation.

2.1.3. Detection model requirements

Several specifications for the practical application of the detection model to support the operators were determined based, among other things, on contact with the Coast Guard (see Appendix A). Specifications concerning operator usage: the implementation of the model should be gradual, the model should instill confidence, be interpretable, be easily explainable, the detection should be fast and accurate and the detection alarm frequency should be limited. Specifications of the detection model concerning application in an operational setting are: a user friendly interface, capable of real-time processing, scalability and capable of integration with other data sources and rules.

2.2. AIS data

2.2.1. International vessel traffic regulations

In 2004, the International Maritime Organization (IMO) adopted a new requirement in the International Convention for the Safety of Life at Sea (SOLAS) regarding AIS. Ships with a displacement of more than 300 tons making international voyages, cargo ships with a gross tonnage of more than 500 making national voyages and all passenger ships are required to have an AIS system on board in permanent operation (with a few exceptions). According to the regulations the AIS system should do the following:

- automatically provide information to appropriately equipped shore stations, other ships and aircraft. This information consists of the ship identity, type, position, course, speed, navigational status and other safety-related information;
- automatically receive this information from similarly equipped ships;
- exchange data with onshore facilities;
- track and monitor ships (IMO, 2024).

2.2.2. AIS data explained

For different times and geographic locations a signal with information is sent by the AIS transponder on the ship, AIS data is in other words geo-spatial temporal data. AIS data consists of static, voyage and dynamic information. Dynamic information is automatically transmitted every 2 to 10 seconds while sailing and every 3 minutes when the vessel is anchored or traveling at speeds below 3 knots. Yang et al. (2024) gave an overview of the AIS messages divided into the field name (subdivided into static, dynamic and voyage-related messages), generation and extra information (see Table 2.1). Generation information is divided into: Set On Installation (SOI), Select From the Pre-installed List (SFPL), Automatically Updated (AU) and Manually Entered (ME).

Table 2.1: AIS messages

Source: Yang et al. (2024)

AIS data		
Field name	**Generation**	**More information**
Static (Update every 6 mins or on request)		
MMSI, call sign, ship name	SOI	might need amending when the ship changes ownership
IMO number	SOI	Unique number for the ship
Length and beam	SOI	Might change if the ship size is changed
Ship type	SFPL	-
Dynamic (2 to 10 seconds or 3 min)		
Position	AU	Longitude and Latitude, accuracy is approximately 10m
Timestamp	AU	Timestamp for the position in UTC
COG, SOG, ROT	AU	Might not be available
Heading	AU	-
Navigational status	ME	-
Voyage-related (Updated every 6 mins or on request)		
Draught	ME	Amended as required
Destination and ETA	ME	Kept up to date as necessary

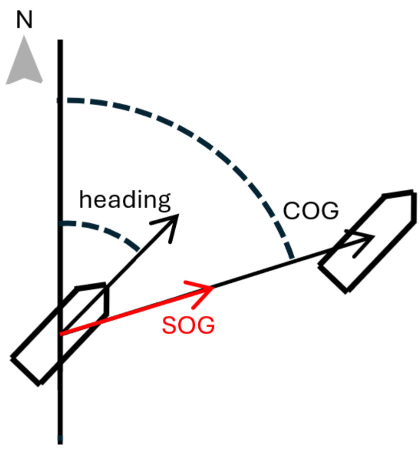

Figure 2.2: Characteristics moving ship

Source: Modified figure from Zagonjolli et al. (2024)

2.2.3. Data quality

Raw AIS data contains deletions, inaccuracies and errors (Wolsing et al., 2022). Information about draugth, navigational status, destination and Estimated Time of Arrival (ETA) are entered manually and can be inaccurate or incomplete. The Maritime Mobile Service Identity (MMSI) -number is intended to be unique, but are occasionally shared with multiple vessels. Sensors update information automatically, but this information may be unreliable when the position fixing system is not properly working or not properly connected to the AIS transponder. When the radio signal is interfered, part of the AIS message can get (partially) lost due to meteorological and magnetic influences. AIS transceivers can be turned off which leads to incomplete data. In addition, AIS signals can be spoofed or manipulated. Finally, the update rates of AIS data are variable and can range from 2 seconds to 3 minutes (Yang et al., 2024).

According to the protocol for AIS data of Kennisprogramma Natte Kunstwerken, information about the ship type or the characteristics (length and width) of vessels is often lacking or filled in with a default value. In addition, the dynamical information regarding heading is not always complete (Zagonjolli et al., 2024).

2.3. Ship movement and behaviour factors

The North Sea is connected to the Northeast Atlantic Ocean (and the Baltic Sea) and is of international importance. Shipping routes connect different countries and continents as efficiently and safely as possible. Shipping movements occur between different ports with the Port of Rotterdam being the largest in Europe. Maritime traffic is divided into route-bound and non-route-bound traffic. Route-bound traffic are merchant vessels and ferries, among others. Non-route-bound traffic are fishing, offshore supply vessels, passenger ships and pleasure craft, among others. In addition to route-bound and non-route bound traffic, vessels have different sizes, speeds and maneuvering characteristics (Ministerie van Infrastructuur en Waterstaat et al., 2022).

2.3.1. Ship motion and degrees of freedom of a ship

The motion of a ship can be described with Course Over Ground (COG), Speed Over Ground (SOG) and heading (see Figure 2.2). The movement of a ship is a result of six degrees of freedom, consisting of three translational motions (surge, sway and heave) and three rotational motions (roll, pitch and yaw) (see Figure 2.3). Different maneuvers a ships can perform are, course keeping, course changing, track keeping and speed changing. According to Bertram (2012), the following main characteristics can be used to describe the maneuverability of a ship:

- Initial turning ability;
- Sustained turning ability;
- Yaw checking ability (ability to stop turning motion);
- Stopping ability;
- Yaw stability (ability to move straight ahead in the absence of external disturbances at one rudder angle).

When a ship has to avoid obstacles at low speed, the stopping ability is applicable. However, in case a ship is traveling at a higher speed, it is more effective to change course instead of trying to stop, as this requires less distance (Bertram, 2012).

The dimensions and weight distribution of a ship influence maneuverability and thus the behaviour of a ship. These differences in behaviour are reflected in the vessel types, as it distinguishes between different purposes of the vessel, corresponding vessel designs and types of cargo.

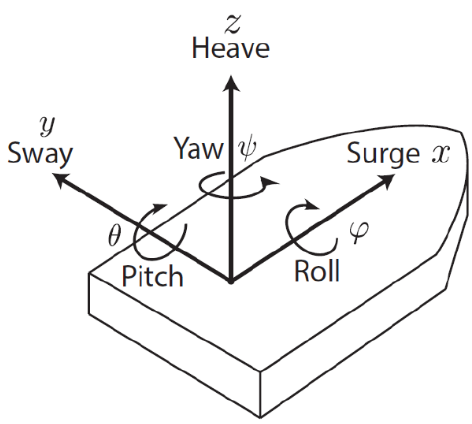

Figure 2.3: Six degrees of freedom of ship

Source: Van Der Steen (2016)

2.3.2. Contributing factors casualty events

The codification by EMSA, mentioned in the Section 2.1 on nautical safety, describes various contributing factors that could potentially lead to accidental events and, consequently, to casualty events (see Figure C.1). European Maritime Safety Agency (2023) divided contributing factors to accident events into three main types:

- External Environment - environmental impact and phenomenon.
- Shipboard operation - i.a. crew resource management, maintenance.
- Shore Management - i.a. operations management, regulatory activities, safety and environment management.

The accident events are divided into: hazardous material, human action, other agent or vessel, system/ equipment failure and unknown. The external environment includes: wind, fog, hydrodynamic effects (e.g. interaction with other passing vessels), current and temperature (EMSA, 2020).

EMSA analysed marine casualties and incidents involving container vessels. The external environment was reported as a contributing factor in 12 investigations, mainly concerning damage to the ship or equipment and . As cited by EMSA (2020): "The following Areas of Concern have been identified:

- **Wind**: Abrupt wind variations, like gales or gusts, affect the vessel directly on its surface, which may cause drift during mooring operations or maneuvering.
- **Fog**: This element has contributed to several navigation accidents, particularly collisions and grounding. Poor visibility, especially in restricted fairways or near the port areas can prove to be detrimental, especially if maximum caution is not demonstrated by the crew and when the recommended tug assistance is not requested.
- **Hydrodynamic effect**: This factor has been reported in three cases where the interactions with other passing vessels, particularly in restricted fairways, contributed to collisions or groundings.
- **Current**: Tidal streams or other currents were reported in two occurrences as factors contributing collision and contact.
- **Temperature**: in one case, it was reported that the high environmental temperature and humidity generated an exothermic decomposition of containerized dangerous goods (thiourea dioxide - Class 4.2, UN 3341) subsequently resulting in a fire."

2.3.3. Contributing factors of navigation accidents

The European Maritime Safety Agency (2022) also analyzed the contributing factors of navigation accidents, like collisions, groundings and contacts. EMSA produced statistics concerning sea area, ship operations and time of accident among others. The time of the incident influences the visibility (during the day or night) and the working set-up (bridge team, boredom, tiredness).

European Maritime Safety Agency (2022) mentions that environmental factors both inside and outside the ship, can affect human performance and contribute to errors or deviations from the normal work path. Such factors have led to collisions and groundings. Areas of concern related to environmental factors that negatively impact safe navigation were identified. In addition to the impact of the external environment from wind, currents, and tides potentially causing drift, visibility issues due to fog and high traffic density were also mentioned. Traffic density can be assumed to dependent on the location, time and season. Aside from the external environment and visibility, the limited maneuverability of the ship (including navigation constraints due to draft), the social environment on board, interference from other ships, and the physical environment on board were also mentioned as areas of concern. Hindrance from other vessels concerns hydrodynamic effects resulting from interactions with passing vessels, which increase the complexity of the environmental dynamics and influence the decision-making process.

2.4. Abnormal safety-concerning behaviour to detect

European Maritime Safety Agency (2023) analyzed the evolution of casualty event types involving ships over the years 2014 till 2022 (see Figure 2.4). The figure shows that in recent years, the most common type of casualty event has been loss of control combined with loss of propulsion power. In addition, collision ranks high, as casualty event. Loss of control in combination with loss of directional control is positioned in the middle of the ranking (other combinations for loss of control are loss of propulsion power and of containment). In this research, we focus on loss of control, i.e. NUC, as mentioned in the casualty events, which could potentially lead to safety consequences and is common (see Figure 2.4). This casualty event is closely linked to drifters, as mentioned in the behaviour patterns, which will be the anomalous behaviour to detect.

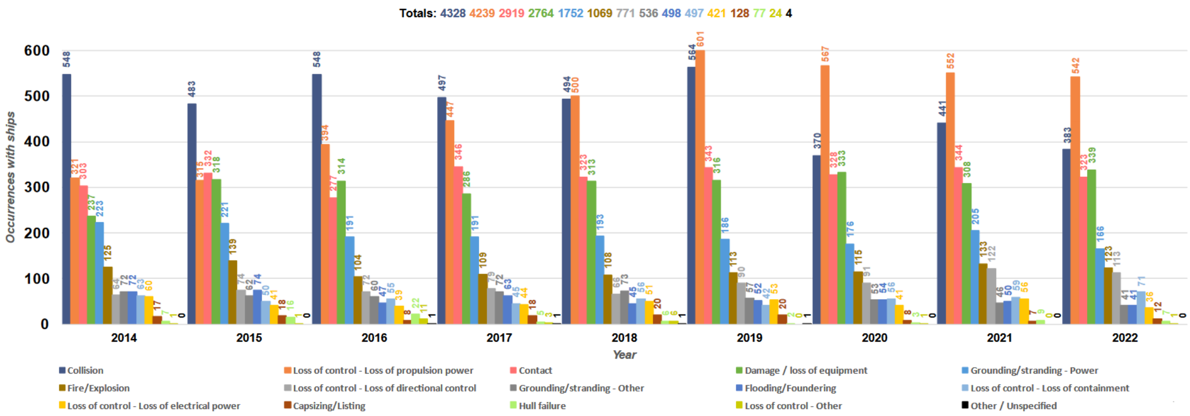

Figure 2.4: Evolution of occurrences with ship, organized by casualty event type from 2014 till 2022

Source: (European Maritime Safety Agency, 2023)

2.5. Summary maritime traffic

The first paragraph on nautical safety addressed various safety-concerning behaviours, focusing on the categorization of casualty events (incidents) and behaviour patterns (anomalous ship behaviour types). The categorization of behaviour patterns will be used as framework for anomalous vessel behaviour (see Figure C.1). In addition, the current methods for signaling the Coast Guard about a ship in distress in an operational setting were mentioned, primarily through communication (i.a. reports from skippers), screen data, and intelligence. To assist the Coast Guard, vessels exhibiting anomalous behaviour can be highlighted after detecting them. Requirements for a detection model to enhance monitoring in the operation setting were listed, and the ability to detect quickly is crucial for this. The following paragraph provided an explanation of AIS data and its quality. Paragraph 2.3 described vessel movements and factors influencing sailing behaviour.

In the last paragraph, drifting was chosen as the anomalous behaviour to be detected in this research. SOG and ROT information from AIS data, are expected to describe drifting motion, among others. In addition, the external environment is mentioned as having an effect on sailing behaviour. For this research, we aim to consider metocean conditions and whether the ship is present in an anchorage area or (the safety zone of) a wind farm.

3

Literature review

This chapter will first zoom in on Machine Learning (ML) and anomaly detection. In the second paragraph, anomaly detection application of geospatial-temporal behaviour will be discussed. Finally, the machine learning approach and methods to enhance operational tools for detecting anomalies is discussed and selected.

3.1. Introduction to Machine Learning and Anomaly Detection

Artificial Intelligence (AI) will be applied to detect unsafe behaviour by means of Automatic Identification System (AIS) data. As Janiesch et al. (2021) defined: ”AI comprises an technique that enables computers to mimic human behavior and reproduce or excel over human decision-making to solve complex tasks independently or with minimal human intervention”. Building analytical models to perform cognitive tasks can be automated with ML. Specifically tasks such as classification, regression and clustering can be applied to high-dimensional data using ML. The process of building an automated analytical model consists of four aspects: data input, feature extraction, model building, and model assessment.

3.1.1. What is Machine Learning?

Machine learning algorithms can be divided into four main categories; supervised, unsupervised, semi-supervised and reinforcement learning (see Figure 3.1). Which algorithm performs best is dependent on the objective and the characteristics of the available data. The data can be structured, unstructured or semi-structured. Examples of machine learning algorithms are classification analysis, regression analysis, data clustering, association rule learning, feature engineering for dimensionality reduction and deep learning methods (Sarker, 2021).

The learning algorithm categories will be elaborated. Firstly, supervised learning which uses labeled training data to train algorithms. Supervised learning is mainly used for classification and regression tasks. Classification can predict distinct class labels by separating the data. With regression a continuous quantity can be predicted by fitting the data. Secondly, unsupervised learning which analyzes data without any pre-existing labels or specifications (unlabeled data). Unsupervised learning is mainly used for clustering, density estimation, feature learning, dimensionality reduction, finding association rules and anomaly detection. A combination of the previous two learning methods, with and without supervision, is semi-supervised learning. This algorithm category uses both labeled and unlabeled data and has been applied to machine translation, fraud detection, labeling data and text classification. Fourthly and finally, reinforcement learning. This algorithm trains software agents by using positive and negative feedback (reward or penalty). This way the optimal behavior is evaluated to improve efficiency. It can be used to increase automation or optimize operation efficiency (Sarker, 2021).

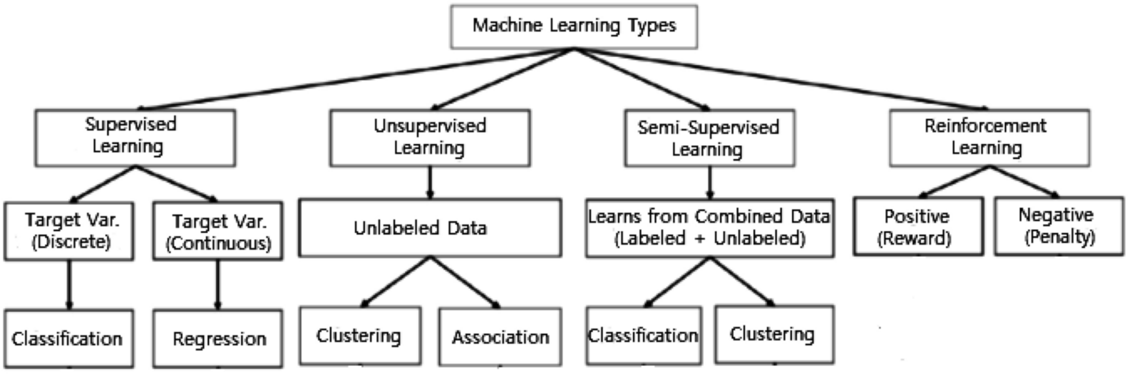

Figure 3.1: Machine learning techniques

Source: Sarker (2021)

3.1.2. What is anomaly detection?

The goal of the project is to detect abnormal behaviour. The overview in Figure 3.2 shows the difference between data considered as normal and data considered as an outlier. The outlier can be subdivided into noise and anomalies, with noise considered a weak outlier and anomalies as strong outliers (Moniz et al., 2024).

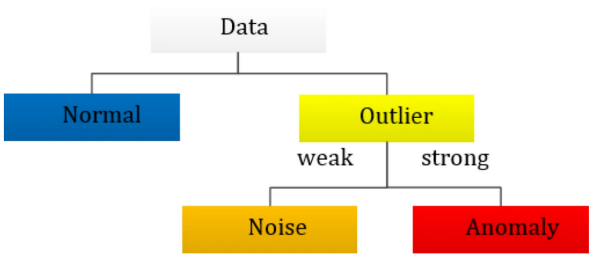

Figure 3.2: Aspect of outliers

Source: Moniz et al. (2024)

Based on availability of data labels, anomaly detection can be classified in 3 ways: use of supervised anomaly detection, semi-supervised anomaly detection and an unsupervised algorithm (see Figure 3.3). The figure clearly shows the separation between normal data and anomalies for supervised and semi-supervised anomaly detection, as the data are labeled. For unsupervised anomaly detection, this distinction is variable and highly dependent on the methods and parameters chosen (Ghamry et al., 2024).

Ghamry et al. (2024) divides anomalies in three groups dependent on their nature :

- Contextual anomalies or conditional anomalies. A data instance that may be considered unusual under certain circumstances. Behavioral characteristics and contextual variables (time and space) are used to identify conditional anomalies.
- Collective anomalies, also identified as group anomalies, which is a set of data items that together deviate from the total data set.
- Point anomalies, which is a single anomalous sample that exhibits deviation from normal behaviour.

Jabbar (2021), gave an overview of unsupervised and supervised anomaly detection algorithms, with the unsupervised category divided into proximity-based and clustering-based detection approaches, each subdivided into global and local outlier detection (see Figure 3.4). The proximity-based outlier detection approach is classified as distance- and density- based. The review explained that different approaches are applicable for local or global outliers, but is not effective for both outlier detection cases.

It concludes that parameter tuning is required to identify local and global outlier objects.

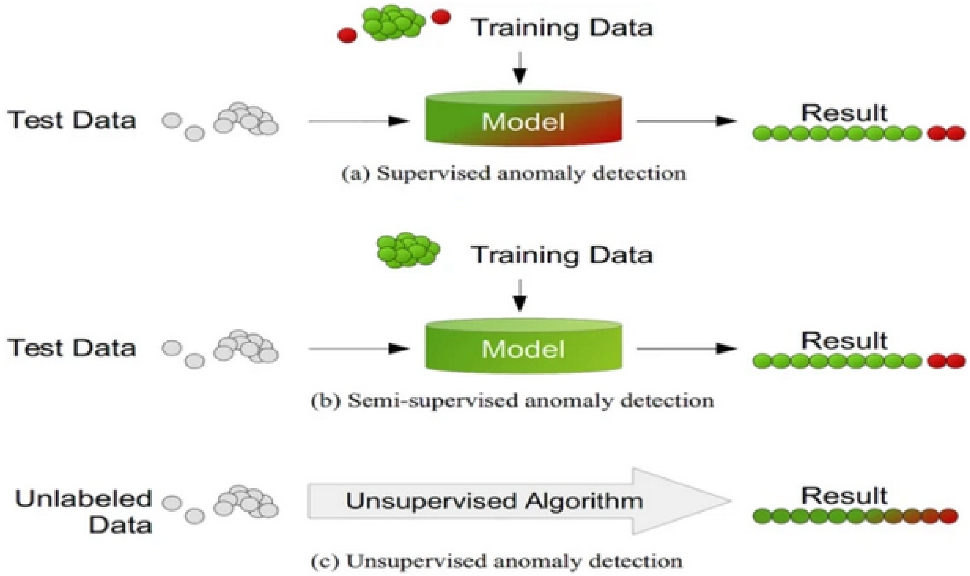

Figure 3.3: Different anomaly detection classifications

Source: Ghamry et al. (2024)

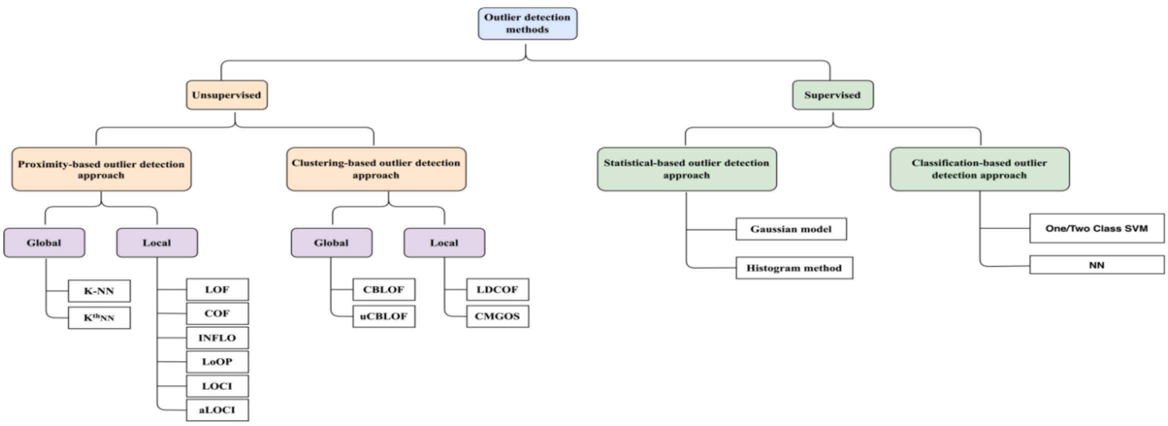

Figure 3.4: Unsupervised and supervised methods divided into different approaches to detect local and global outliers

Source: Jabbar (2021)

3.1.3. Supervised versus unsupervised

An example of anomaly detection in a field other than maritime is the research by Weijler et al. (2022). In this research a semi-supervised approach, is used on data of acute myeloid leukemia flow cytometry in combination with implicit expert knowledge. This one-class classification approach is based on the dimension reduction technique Uniform Manifold Approximation and Projection (UMAP) applied with a local distance metric. Clusters are defined with the density based clustering technique Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN). Subsequently, blast clusters are identified based on the number of control-events in the cluster, specifically those with a very low number of control-events.

For this research AIS data is applied. The choice for an unsupervised or supervised ML approach depends on the availability of pre-labeled datasets. At the start of this research, no labeled AIS data were available for use. Therefore, unlabeled AIS data will be used for the model, implying the use of unsupervised machine learning. In addition, this research focuses exclusively on point anomalies. This choice is made due to time constraints and the limited amount of AIS used to show the validity of the model. With a limited amount of AIS data, fewer groups (or clusters) exhibiting similar behaviour are expected, leading to less reliable results for global detection.

3.2. Anomaly detection in AIS data

AIS data can be used to analyze maritime traffic. The data is used in different research areas like traffic, logistics and transport economy, monitoring, collisions, emission, oil spills, noise, interaction with whales, fishing and ice (Svanberg et al., 2019). Anomaly detection is a known research topic for AIS data as well. Yang et al. (2024) concluded that the majority (90%) of the papers focused on deviation from normal routes. A distinction was made between a clustering-based model and a neural network-based model.

3.2.1. Anomaly detection with a clustering-based model

In distinguishing abnormal and normal trajectories using unlabeled AIS data, clustering is very effective. Clustering can be performed using methods such as Density-Based Spatial Clustering of Applications with Noise (DBSCAN) and K-means, among others.

Palotta & Jousselme (2015) used Traffic Route Extraction and Anomaly Detection (TREAD) with a DBSCAN procedure, to extract valuable information for decision-making with unsupervised ML on AIS data. Additional features for anomaly detection were incorporated, like position of ships and kinematic features. Off-route vessels were detected with positional information and on-route vessel anomalies were identified with COG and speed information.

According to Fernandez Arguedas et al. (2018), density-based clustering methods are convenient in maritime applications, because the number of clusters does not need to be pre-set and clusters of arbitrary shapes can be detected. They proposed a method to automatically produce maritime traffic representations from historical self-reporting spatial data. Based on analysis of waypoints and routes the maritime traffic network was created and behaviour patters inherent to spatio-temporal information were extrapolated. Eventually, deviations from the declared route could be detected (anomaly).

An extension of DBSCAN, namely Density-Based Spatial Clustering of Applications with Noise considering Speed and Direction (DBSCANSD), was porposed by Liu et al. (2015). Vessel movements were associated with International Maritime Organization Rule, like Traffic Separation Scheme (TSS) boundaries. Anomalous navigational behaviors could be detected with three division distances with the clusters. The method considered longitude, latitude, speed and direction, to determine for each trajectory point if the vessel was anomalous.

The research of Guo et al. (2021) is an example based on K-means clustering. An improved method called K-means++, is used for clustering error weights of AIS data points. This method (K-means++) is applied to ensure that the the initial clustering centers are as far apart as possible. In this way, the influence of the selection of the first cluster center on the cluster result, is reduced. Subsequently, noise and outliers can be detected automatically with the clustering method. To detect all anomalies, a loop detection process, by repetition of kinematic estimation (with longitude, latitude, SOG and COG), and error clustering process, is introduced.

3.2.2. Anomaly detection with a neural network-based model

B. J. Rhodes et al. (2007) applied a neural network-based model, to use real-time tracking information to simultaneously learn motion pattern models. The present motion states were used to evaluate the behavior patterns of vessels. They explain event-level learning in which normal events, for example dependent on class of vessel and environmental conditions, are learned and deviations can be detected. Secondly, inter-event learning was described as learning links between behavioral events to predict future position of a vessel given present behavior information, location and velocity (course and speed). A uniform square grid of the area was used to enable learning to be contextually specific to vessel behavior. In addition, vessel reports were split in 3 minutes for a temporal horizon of 15 minutes. In summary, a method to detect anomalous vessel event behaviour and predict vessel locations in a port was improved and applied for associative learning (rule-based) and making predictions of future vessel locations.

3.2.3. Framework for detecting and classifying abnormal behaviour

A framework can be used to implement selected machine learning methods within a detection approach. Rong et al. (2024) presents a data-drive approach for learning maritime traffic normalcy model and detecting ship abnormal behaviour, explained within a framework (see Figure 3.5). This research provides three examples for detection approaches, using abnormal point detections and a method for detecting and classifying ship abnormal behaviour in ship trajectories based on features. Profiles are generated of independent motion parameters, namely COG, speed and lateral distance to ship route (see second block in framework in Figure 3.5). Ship trajectories are grouped based on matching itinerary with a similarity-based clustering algorithm (see (a) Ship route extraction in Figure 3.6). Each group has a lateral distance (from ship location perpendicular to the route center line), speed and direction (COG) distribution. A normalcy model, for the ship route, is estimated by a series of these Gaussian distributions (see (b) Ship route characterization in Figure 3.6). More specifically, the lateral distance distribution is used to define the route boundary, and offroute behaviour is detected. In addition, the speed and COG distributions help to identify ship speed and direction that are incompatible with the ship's route. These anomalous ship points are detected when a point deviates from the standard neighboring points, with the same ship route, exhibiting similar speed and direction. With the Kernal Density Estimation (KDE) method the probability density function of the variables, speed and COG, are estimated in which the abnormal points of ships correspond to low densities (see (c) Abnormal points detection in Figure 3.6). Using a sliding window approach, motion profiles (speed, COG and lateral distance) of parts of the trajectory in historical AIS data, are captured (see third block in framework in Figure 3.5). A window is flagged as abnormal by comparing these motion parameters with pre-defined threshold (rules), specifically the route boundary as well as the density threshold derived from the probability density functions of speed and COG. Subsequently, a time interval is extracted for the occurrence of the abnormal behaviour, namely offroute, speed- and heading not compatible with the route (see (d) Abnormal point types considered in this study in Figure 3.6).

For the classification model Rong et al. (2024) used clusters of features capturing the observed ship's abnormal behaviour (see fourth till sixth block in framework in Figure 3.5). The following features were proposed for extraction: standard deviation of the speed, detour factor, maximum drift angle, accumulative COG change, delta COG, maximum lateral distance. First, the features are extracted of the historical abnormal behaviours and normalized. Subsequently, clusters are generated using a density-based clustering method, specifically DBSCAN, which groups data into objects with similar features. DBSCAN generates clusters of elements based on the density of points in their neighborhood, classifying points as core points, density-reachable points and noise. After clustering the features, each trajectory and feature vector are labeled with a cluster number representing a specific behaviour pattern. With Random Forest (RF) classification, the labeled feature vectors are used to train the multi-class classification model. The four types of abnormal ship behaviour, correspond to four clusters. The clusters include trajectories with characteristics based on the extracted features (see Table 3.1). A confusion matrix was generated to evaluate the performance of the trained RF classification model. SHapley Additive exPlanations (SHAP) is used as an Explainable Machine Learning (EML) method to provide insight into the machine learning model, which can be regarded as a black box. SHAP shows how each feature affects the model's output.

Table 3.1: Ship abnormal behaviour types and their characterizing features

Abnormal ship behaviour	Extracted features characteristics
Circular	Speed decreasing, accumulative COG around 2π, delta COG small
U-turn	accumulative COG and delta COGaround π
Double U-turn	large detour factor, accumulative COG and delta COG small
Off-route	maximum lateral distance exceeds 1 or -1

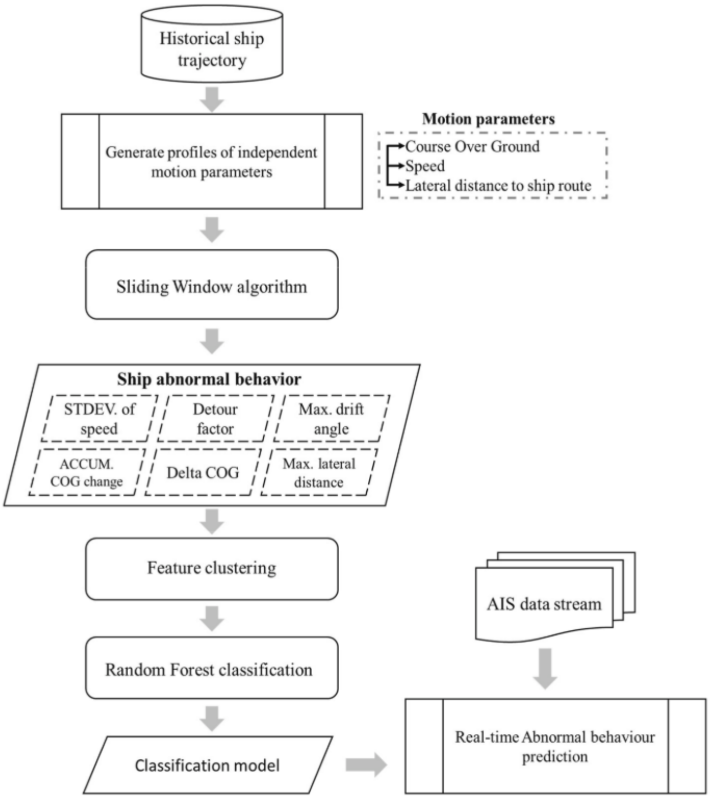

Figure 3.5: Data-driven approach for learning a maritime traffic normalcy model and detecting abnormal ship behaviour, explained within a framework

Source: Rong et al. (2024)

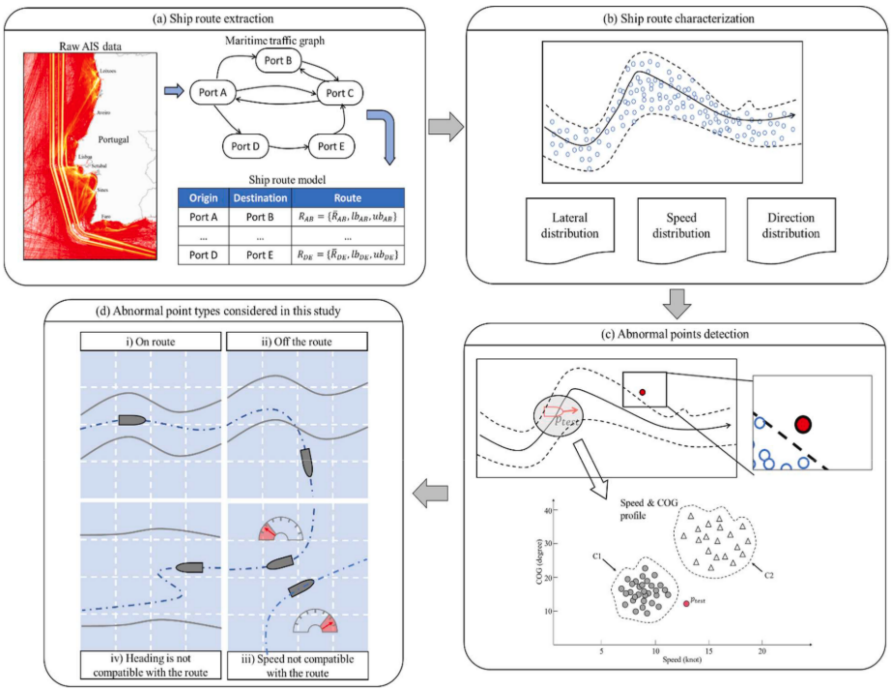

Figure 3.6: (a) Ship route extraction, (b) Ship route characterization, (c) Abnormal points detection and (d) Abnormal point types considered in this study

Source: Rong et al. (2024)

3.3. Detection approach and method selection

To develop a model that enhances operational tools for detecting anomalies, a machine learning approach and appropriate methods should be selected. At the end of Paragraph 3.1, unsupervised machine learning was selected for the detection approach, and the detection will be limited to point anomalies. In the previous paragraphs, several detection approaches were mentioned for unsupervised machine learning, namely clustering-based, network-based and proximity-based. The proximity-based model was divided into distance and density-based. For this research a density-based method will be used for the local outlier detection. To develop a framework for the detection model, model steps and machine learning methods should be selected.

3.3.1. Guideline for model steps till clustering of AIS data

The model of van Engelen (2023) applied machine learning techniques to AIS data to cluster similar vessel behaviour on inland shipping. The vessel behaviour is characterized by extracting features from vessel trips based on AIS data logs, such as speed, acceleration, direction, maneuverability, and position-related features. Data of trips, characterized by their features, were reduced in two dimensions by the UMAP algorithm. With K-means clustering, clusters were generated exhibiting similar behaviour, in other words similar feature characteristics. This model gave a promising start for the detection of anomalous behaviour for the North Sea.

3.3.2. Time series feature engineering

To generate meaningful features from AIS data, time series characterization methods can be applied, which was done in the research of Christ et al. (2018). To save time in identifying and extracting meaningful features from time series, the Python package Time Series FeatuRe Extraction on the basis of Scalable Hypothesis tests (tsfresh) was developed. This package integrates 63 time series characterization methods, thereby automatically calculating 794 time series features, with feature selection. The package utilizes machine learning libraries and standard Application Programming Interface (API) of timeseries.

3.3.3. Dimension Reduction technique

Several dimension reduction techniques can be applied, including Principal Component Analysis (PCA), t-Stochastic Neighborhood Embedding (t-SNE) and UMAP. Mcinnes et al. (2020) explained that UMAP is faster and offers better scalability then t-SNE. UMAP compared to PCA is better in finding and preserving the local structure in data. In short, UMAP successfully reflects much of the large scale global structure that PCA represents well, while preserving local fine structure, like t-SNE. Narayan et al. (2020) mentions in his research that t-SNE and UMAP neglect information about the local density of data points in the source data. This results in a poor distinction in the visualization of data points and their close-by neighbors, in contrast to their far off neighbors. The research proposes density-preserving data visualization methods, namely den-SNE and densMAP, build upon t-SNE and UMAP respectively. The embeddings showed that both local structure and variability were preserved in the original data.

For this research a dimension reduction technique is preferred that groups trips with the same features well, has a good performance, and preserves the density of the data, therefore densMAP is chosen. DensMAP will be used to create a two-dimensional embedding to make the model better explainable (EML).

3.3.4. Outlier detection technique

Jabbar (2021) provided an overview of outlier detection methods. The un-supervised, proximity-based, and subsequently density-based method was chosen. Based on the review of Jabbar (2021) and the decision for local outlier detection, several methods are mentioned (see Figure 3.4). The methods for local outlier detection are Local Outlier Factor (LOF),Connectivity-based Outlier Factor (COF), INFLO, Local Outlier Probabilities (LoOP), LOCI and aLOCI. For this model the Local Outlier Factor (LOF) will be chosen, because it is already implemented in Python.

4
Materials and Methods

In the previous chapter a literature study was done for anomaly detection with machine learning and AIS data. Different approaches and methods for anomaly detection were mentioned and selected. This chapter explains how the detection model is composed of different steps, illustrated using a Flowchart (ISO 5907, 1985), and where the chosen methods will be applied. In Section 2.1, model requirements for the detection method were mentioned. In addition to anomaly detection, the requirements of explainability and scalability are addressed.

4.1. Materials

For the model the programming language Python in combination with machine learning techniques is applied on AIS data. An anonymized AIS dataset has been made available by the Coast Guard (or RWS) to the TU Delft for research purposes. The AIS data covers 31 January and 1 February of 2022 and an area of the North Sea (visible in Figure 4.1). Information about spatial areas in the North Sea are obtained with Quantum Geographic Information System (QGIS) (Free Software Foundation, 1991) (see Table E.5 and Figure E.1 for an overview). The metocean conditions were obtained from the ERA5 data, which provides hourly estimates for a large number of atmospheric and ocean wave quantities, among others (Hersbach et al., 2020). Several Python libraries are used: GeoPandas (GeoPandas developers, 2013), MovingPandas (MovingPandas develeopers, 2024) scikitlearn (scikit-learn developers, 2007) and holoviews (Holoviz contributors, 2024). In addition, the following Python packages have been applied: Shapely (Sean Gillies and Shapely contributors, 2024), tsfresh (Maximilian Christ et al., 2024) and umap-learn (Mcinnes et al., 2020).

4.2. Conceptual framework

The approach of the detection model consists of generating trips, subsequently features are created for each trip. The trips with their corresponding features are represented on an embedding and finally the outliers are detected. A simplified framework of this approach is visible in Figure 4.2. The model for this research, representing the approach, consists of six steps to get from AIS data logs to outliers. Each Section in the report represents a step in the model (see Figure 4.3) and a separate framework has been created for each model step. First, trips of vessels were created from the AIS data logs (Section 4.3). Second, a feature table is generated with motion characteristics for each trip (Section 4.4). Subsequently, information of the ship's location, i.e. spatial properties, is included as a feature (Section 4.5). The metocean conditions of the trip is added as feature in Section 4.6. As fifth, dimensional reduction is applied with densMAP and an embedding is generated (Section 4.7). Lastly, anomalies are detected with the LOF (Section 4.8). To better understand the data in the embedding and the designated outliers, these will be visualized (Section 4.9), i.e. EML. A summary of the key adjustments of the model are named in Section 4.11.

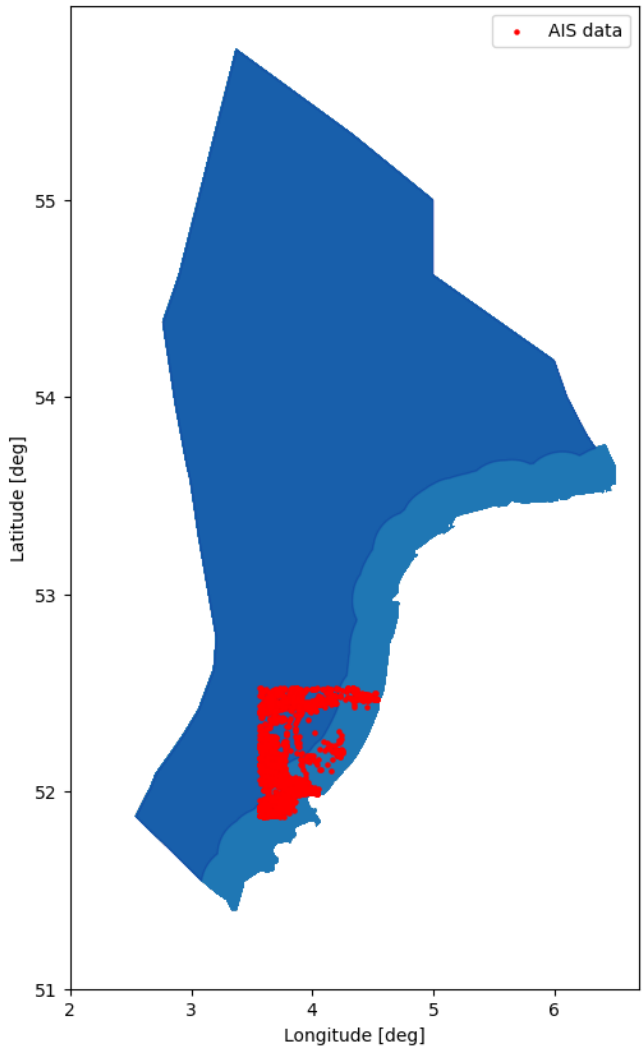

Figure 4.1: AIS dataset covering area in the North Sea, including the EEZ area (dark blue)

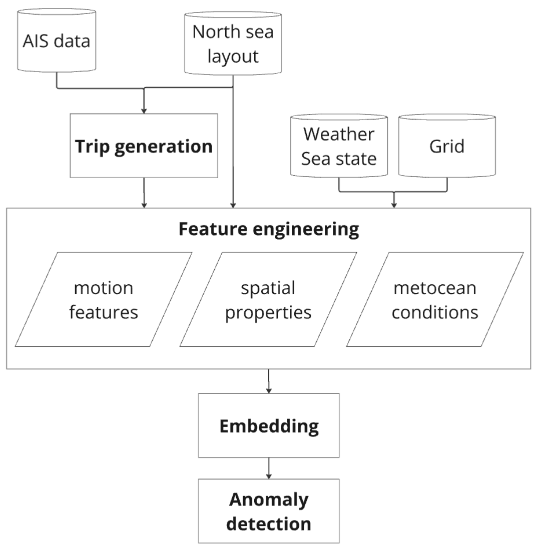

Figure 4.2: Simplified framework research model

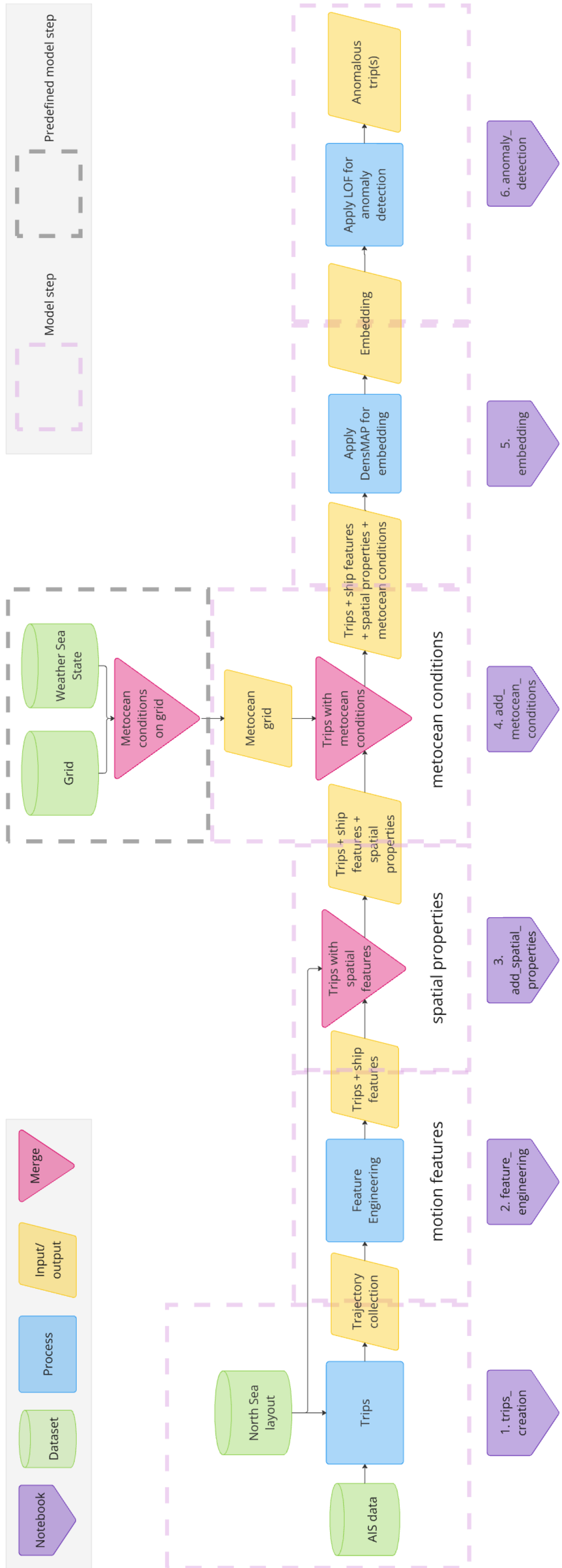

Figure 4.3: Model framework with six method steps

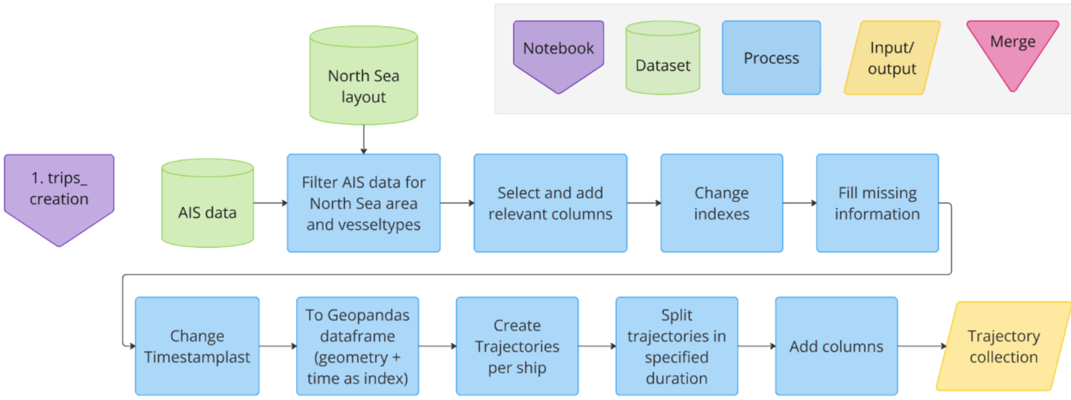

Figure 4.4: Trips creation steps

4.3. Trips creation

The first model step turns AIS data logs into one or more trips per vessel (see Figure 4.4). This results in a trajectory collection. A trajectory collection is a collection of trajectories of the same duration from all ship voyages. Thereby, the voyage of one ship may consist of multiple trajectories.

4.3.1. Filtering

As mentioned before AIS data contains a lot of information (see Table 2.1 and Table E.1 for units).The relevant data is filtered according to the scope of this research, which concerns the North Sea area and type of vessel. A polygon of the North sea is used to filter on the North Sea area (see dark blue area in Figure 4.1). With *shapely.intersects* package the ship locations within the North Sea polygon are retained. For the current AIS dataset, this means that AIS data located on inland waterways will be filtered out. The data contains information about the vessel type by means of the 'vesseltype' code and the 'vesseltype ERI' code, which is relevant for seagoing vessels and inland vessels respectively. The vessel type codes covering cargo (and tanker) vessels are 70 up and including 89, 1003, 1004, 1016, 1017 and 1024 (see Appendix D).

4.3.2. Data pre-processing

Before the AIS data can be used to generate trajectories, the data needs to be pre-processed. Chapter 2 discussed the data quality of AIS data, which is used to select the relevant and fairly reliable columns for the model (see Table 4.1). In addition, indices are adjusted, the (vessel)name is copied for later use, vesseltype codes are adjusted (vesseltype and vesseltype ERI) and missing values for the length and width have been filled in.

Table 4.1: AIS data columns selection, data pre-processing

	Static and Voyage related information	**Dynamic information**
Used	name	sog, latitude, longitude, timestamplast
Adjusted and used	vesseltype	ROT
Not used	vesseltypeERI, hazardouscargo, eni, imo, nationality, eta, callsign, traj_id, tobow, tostern, toport, tostarboard, length, width, draughtMarine, draughtInland	cog, maneuver, seconds, heading, headingValid, mmsi

4.3.3. Trips collection

To make trajectories from AIS data logs the dataframe needs to be converted to a Geopandas GeoDataframe with GeoPandas(GeoPandas developers, 2013) by adding geometry points of the longitude and latitude data with the Common Reporting Standard (CRS) set as *ESPSG:4326* . This is equal to the World Geodetic System of 1984 and earth centered, e.g. WGS 84 (MapTiler, 2024). Subsequently, the timestamplast was set as index and converted to no timezone.

Using MovingPandas (MovingPandas develeopers, 2024) and the previously defined geometry points, one trajectory per shipname (i.e. per ship) were created. Subsequently, the trajectory of each ship was split with the *ObservationGapSplitter* when the trajectory showed a gap. This is necessary, otherwise a trip sailing outside the defined area, following that returning to the area, is wrongly connected. The trip is split in case the trajectory showed a gap in time of 5 min and a minimum length of 100m. AIS data is received per approximately 2- 10 seconds for sailing ships and 3 minutes for ships at anchor (see Chapter 2). The length of 5 minutes is chosen, because at least one signal should have been received within these 5 minutes. In addition to splitting the trips based on observed gaps, the trips per vessel are split based on a defined origin in time and time intervals (e.g. 60min). First and foremost, this is important because the trajectories have the same length in order to compare them fairly. In addition, a start time and duration of the trajectory are used to determine the speed of the detection. These steps resulted in a *TrajectoryCollection* (see Figure 4.6).

4.3.4. Adding columns

As last step, columns are added with MovingPandas functions and manually (see Table E.2 for options). The speed, angular difference and time elapsed are added to calculate new values for the ROT. To calculate new values for the ROT, the speed, angular difference and time elapsed are needed. The speed is added with *movingpandas.TrajectoryCollection.add_speed*, in CRS units per second. The angular difference is added with *TrajectoryCollection.add_angular_difference*, in degrees between 0 and 180. The difference in seconds between the timestamps per trip are calculated and added as the time_elapsed_seconds column. The ROT is calculated as the change in direction (angular_difference) divided by the difference in time in minutes (using time_elapsed_seconds devided by 60). The ROT is set to zero when the value is higher than 250 or lower than -250. In addition, ROT is set to zero when the time difference is greater than 20 minutes and the velocity is less than 0.6 units per second. The additional columns with values and units are shown in Table 4.2.

Table 4.2: AIS data, additional columns added with functions of MovingPandas (f) or manually generated (m)

Source: (MovingPandas develeopers, 2024)

Additional columns AIS data		
Data columns	**Description**	**range and or unit**
angular_ difference (f)	Calculated as the absolute smaller angle between the direction for points along the trajectory.	0 till 180.0 degrees
speed (f)	Computed between the current point and the previous point.	meter/sec
time_elapsed _seconds (m)	Time elapsed between 2 signals.	seconds
ROT (m)	Newly defined ROT instead of original rot. Angular difference from previous signal to current signal divided by the time elapsed in minutes.	degrees/minutes

4.3.5. Results trips creation

This model step, trip_creation, ended in a trajectory collection. The dataset started with 4,286,380 AIS data logs (see Figure 4.5). The trajectory collection with trips of a duration of 30 and 60 minutes consisted of 3,427 trips and 5,879 trips respectively. An example of the columns after creating the trips are visible in Figure 4.6 and the additional columns can be seen in Figure 4.7. A ship with its unique name ('shipname_original') can have multiple trajectories, which are described with a trip identification name ('shipname'). In this trip identification name, the name of the vessel and the start date and time of the trip is visible. One unique shipname has multiple timestamplast's, since multiple AIS data logs, which are updated around every 2 seconds to 3 minutes, can belong to one trajectory with a duration of, for example, 30 or 60 min.

	sog	heading	callsign	vesseltype	rot	timestamplast	name	vesseltypeERI	heading	traj_id
0	0.1	0.0	PH13280	80	0.000	2022-02-01 15:30:56+00:00	testschip-1328	8022	0.0	6988
0	2.2	0.0	PH35490	89	0.000	2022-01-31 18:02:30+00:00	testschip-3549	8020	0.0	25130
0	15.9	80.0	PH27190	71	-0.714	2022-02-01 05:37:50+00:00	testschip-2719	0	80.0	24672
0	1.2	326.0	PH59950	70	0.000	2022-01-31 15:30:21+00:00	testschip-5995	0	326.0	36862
0	7.9	0.0	PH19370	70	0.000	2022-01-31 23:09:33+00:00	testschip-1937	8010	0.0	11605

Figure 4.5: Original AIS data

timestamplast	shipname	shipname_original	vesseltype	latitude	longitude	geometry	sog
2022-02-01 16:09:11	testschip-1002_0_2022-02-01 16:00:00	testschip-1002	79	52.293930	3.565162	POINT (3.56516 52.29393)	16.900000
2022-02-01 16:09:18	testschip-1002_0_2022-02-01 16:00:00	testschip-1002	79	52.294350	3.565457	POINT (3.56546 52.29435)	16.900000
2022-02-01 16:09:23	testschip-1002_0_2022-02-01 16:00:00	testschip-1002	79	52.294712	3.565703	POINT (3.5657 52.29471)	16.700001

Figure 4.6: Dataframe after creating a trip collection

timestamplast	shipname	angular_difference	time_elapsed_seconds	ROT	speed
2022-02-01 16:09:11	testschip-1002_0_2022-02-01 16:00:00	0.000000	NaN	NaN	7.264228
2022-02-01 16:09:18	testschip-1002_0_2022-02-01 16:00:00	0.000000	7.0	0.000000	7.264228
2022-02-01 16:09:23	testschip-1002_0_2022-02-01 16:00:00	0.747064	5.0	8.964767	8.734652

Figure 4.7: Dataframe with additional columns

4.4. Feature engineering - motion features

In this section the transformation of the trajectory collection to the combined feature data frame will be elaborated, i.e. feature engineering of the motion features (see Figure 4.8). The combined feature table is a combination of features that are manually made and features that are generated with the help of the Python package *tsfresh* (Maximilian Christ et al., 2024). The tsfresh package is used to generate motion features of vessels, by means of the time series of the trajectories. The features that are manually generated will describe characteristics of the ship and its trajectory. Per trip multiple features are generated. Which features are potentially relevant is discussed in Chapter 2.

4.4.1. Manually added

In this step, some information of the trip collection dataframe is passed as a list (latitude, longitude, timestamplast, time_elapsed_seconds). In addition, information is passed as a single value (vesseltype, shipname and shipname_original). The vessel type of the trajectory can be included as a binary code for vessel type groups, by defining the vessel type code (such as 70) as belonging to the cargo ships (= 1/ yes) and belonging to the fishing ships (= 0/no). Another example of a manually made feature with a binary code is the time of the day, sails the vessel during morning, afternoon, evening or nigth. Finally, features can be created by defining and applying a manually made function, e.g. for calculating the length to width ratio. This information is stored in a dataframe which shows the information as features per trip with its unique shipname (see Figure 4.9).

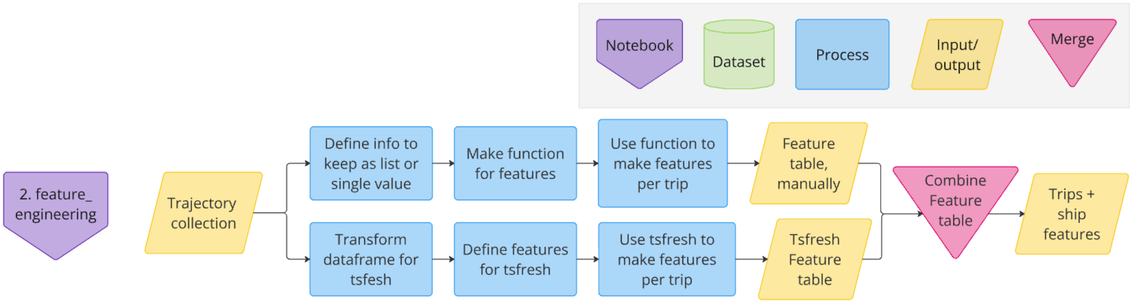

Figure 4.8: Feature engineering steps

	latitude	longitude	timestamplast	time_elapsed_seconds	vesseltype	shipname	shipname_original
0	[52.29393005371094, 52.294349670410156, 52.294...	[3.565161943435669, 3.565457105636596, 3.56570...	[2022-02-01T16:09:11.000000, 2022-02-01T16:09:...	[nan, 7.0, 5.0, 6.0, 7.0, 5.0, 7.0, 6.0, 4.0, ...	79	testschip-1002_0_2022-02-01 16:00:00	testschip-1002
1	[51.936161041259766, 51.93618392944336, 51.936...	[3.565268039703369, 3.5654819011688232, 3.5657...	[2022-02-01T07:30:08.000000, 2022-02-01T07:30:...	[nan, 3.0, 3.0, 3.0, 4.0, 2.0, 7.0, 1.0, 2.0, ...	70	testschip-1024_0_2022-02-01 07:00:00	testschip-1024
2	[51.96994400024414, 51.969966888427734, 51.970...	[3.7996881008148193, 3.799876928329467, 3.8001...	[2022-02-01T08:30:03.000000, 2022-02-01T08:30:...	[nan, 1.0, 3.0, 4.0, 6.0, 1.0, 3.0, 2.0, 5.0, ...	70	testschip-1024_0_2022-02-01 08:30:00	testschip-1024

Figure 4.9: Example dataframe manually made features

4.4.2. Generated with tsfresh

A selection of the features that can be computed with tsfresh are the mean, median, standard deviation, skewness, kurtosis, sample_entropy, maximum, minimum, quantile (0.1, 0.2, 0.3, 0.4, 0.6, 0.7, 0.8, 0.9) for the parameters SOG and ROT. Skewness is a measure of the asymmetry of a distribution and needs at least three values. Kurtosis describes the shape of the tail of a distribution compared to the overall shape of the distribution and needs at least four values. Before tsfresh is applied, the line segments of the trip collection will be transformed to a GeoDataFrame. The relevant information (e.g. ROT, SOG) is then passed to the function which makes features with the help of tsfresh. This results in single values for the defined features per shipname (i.e. trip identification name).

4.4.3. Combining manually and tsfresh features

Finally, the features will be combined into one feature table based on the unique shipnames. Which is result of this model step, feature engineering.

4.5. Feature engineering - spatial properties

In this method step, information is added, as a feature, about the areas where the ship was located during the trip, i.e. spatial properties (see Figure 4.10 and Table E.4).

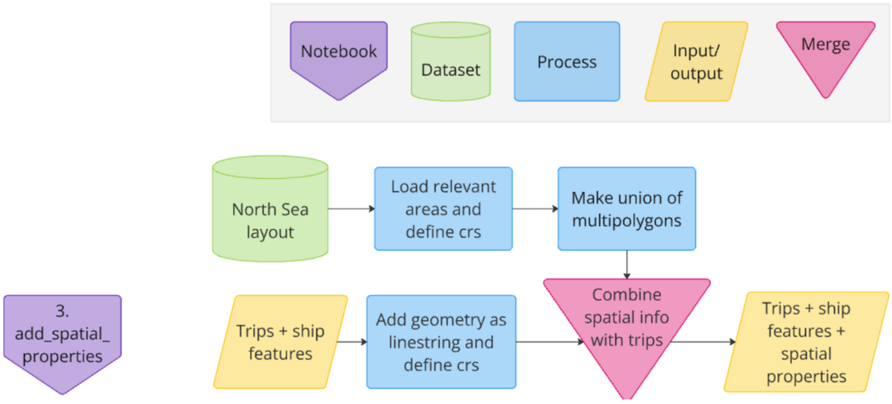

Figure 4.10: Steps of adding spatial properties as features

Information on spatial areas was obtained using QGIS (Free Software Foundation, 1991). The following spatial areas are selected (see also Figure 4.12):

- Permitted wind farms safety zones (dark green in figure)
- TSS (blue in figure)
- Approach area (light green in figure)
- Anchorage area (pink in figure)

When the areas are loaded, the CRS should be defined (European Petroleum Survey Group (EPSG):4326), to make the trips and areas compatible. The geometry of the areas consist of MultiPolygons (for permitted wind farms safety zones, approach area and anchorage area) and MultiLineStrings (for TSS).With *geopandas.GeoSeries.union_all* returns a geometry of the areas containing the union of all the geometries. This allows trips to be compared to the areas in one step. For this step, the feature table must also be modified. With *geopandas.points_from_xy* a linestring is added as the geometry of the feature table. In addition, the CRS is defined for the trips (EPSG:4326). Now the trips can be compared using the functions *shapely.intersects* and *shapely.crosses* for the MultiPolygons and MultiLineStrings geometries respectively (Sean Gillies and Shapely contributors, 2024). These functions use two geometries to check the spatial relation and returns a boolean variable. The Dimensionally Extended Nine-Intersection Model (DE-9IM) is used to describe the spatial relation between these geometries (e.g. intersect, touch, contain, equal). The intersects function returns 1 if the boundary or interior of the object (trip) intersect with those of the other (areas geometry), i.e. trip being inside the area. The crosses function returns 1 if the object (trip) intersects the interior of the other (areas geometry) but does not contain it, and the dimension of the intersection is less than the dimension of the one or other, i.e. trip crossing the TSS line. Finally, the spatial relationship per trip to different areas is added to the feature table as a location feature (see Figure 4.11).

	shipname	shipname_original	in_anchorage	in_approach_area	in_wind_safety_zone	TSS_crossing
0	testschip-1002_0_2022-02-01 16:00:00	testschip-1002	0	0	0	1
1	testschip-1024_0_2022-02-01 07:00:00	testschip-1024	0	1	0	0
2	testschip-1024_0_2022-02-01 08:30:00	testschip-1024	0	1	0	1

Figure 4.11: Example dataframe of spatial properties as features

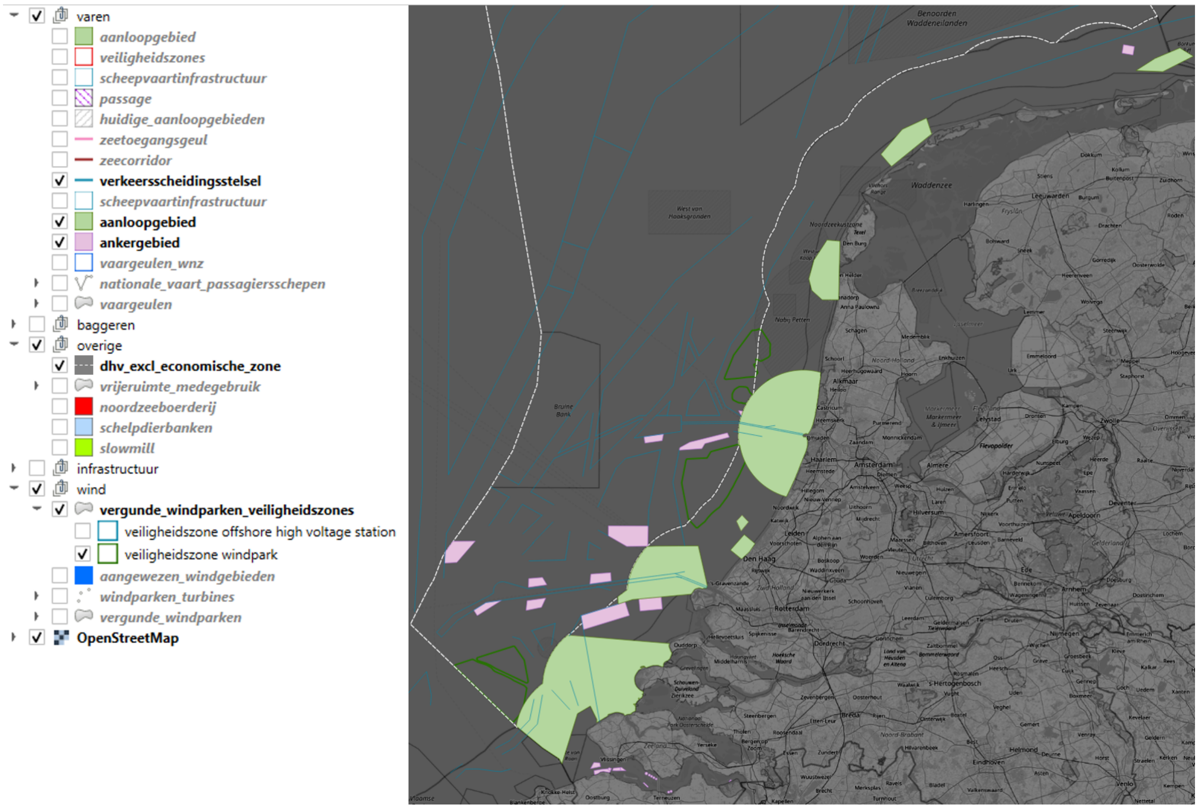

Figure 4.12: Selected spatial properties

Source: (Free Software Foundation, 1991)

4.6. Feature engineering - metocean conditions

In this model step, metocean conditions during each trip are added as environment feature (see Figure 4.13). The metocean conditions (from ERA5) consists of the following data, depending on the location and time (hourly): velu, velv, swh, mwd, u10 and v10 (see Table 4.3) (Hersbach et al., 2020).

To be able to couple the right metocean conditions to the trip, the location and time of the metocean conditions is compared to the location and time of the trip. But first, filtering is done on the time span for which conditions are needed. Subsequently, a polygon with a defined CRS (EPSG:32631) is added which is obtained from the polygon_wkt column using the *geopandas.GeoSeries.from_wkt* function. To be compatible to the trips, the CRS of the polygon is converted to the same EPSG as the trips (i.e. EPSG:4326) and set as index for the metocean conditions GeoDataFrame. In addition, a selection is made of the columns that are relevant (velu, velv, swh, mwd, u10 and v10). The trips must also be adjusted to be able to add metocean conditions.

The midpoint of the timestamp of the trip is assigned as *middle_timestamp* column. Then the associated location is added as a point as *middle_trip* column and defined as active geometry. Finally, the *middle_timestamp* will be rounded to whole hours, named as *rounded_time* and defined as an index. The *middle_timestamp* is rounded to whole hours, since the metocean data is defined per hour. With *geopandas.sjoin*, the metocean conditions based on time and location can be added to the feature table of the trips as single values.

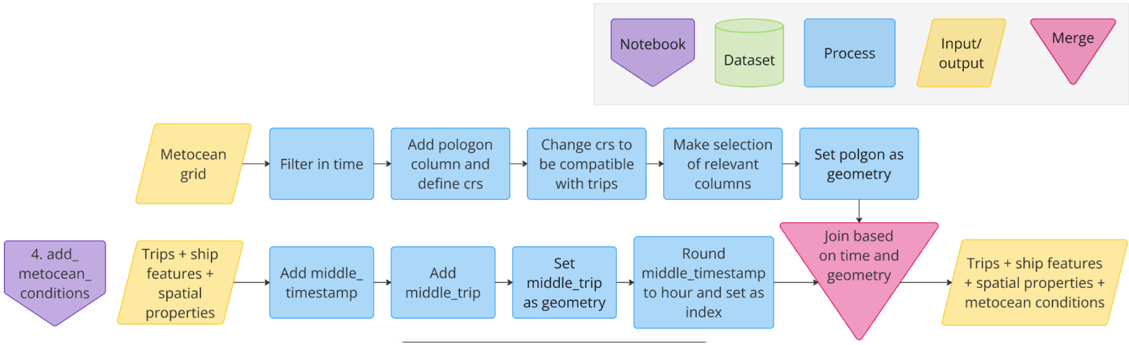

Figure 4.13: Metocean conditions steps

Table 4.3: Metocean conditions variables

Source: (Hersbach et al., 2020)

Metocean conditions	Description	Unit
velu	Eastward component velocity	m/s
velv	Northward component velocity	m/s
swh	Significant height of combined wind waves and swell	m
mwd	Mean wave direction	degrees
u10	Eastward component (u-direction) of the wind at a height of 10 meters above the surface of the earth	m/s
v10	Northward component (v-direction) of the wind at a height of 10 meters above the surface of the earth	m/s

4.7. Embedding - dimension reduction technique

Dimension reduction will be applied in this section, which will result in an embedding of the trips with their distinctive features (see Figure 4.14). Dimension reduction can reduce the number of features in the dataset while simultaneously preserving necessary information, subsequently data can be visualized. In Chapter 3, it was decided to use densMAP for the dimension reduction technique.

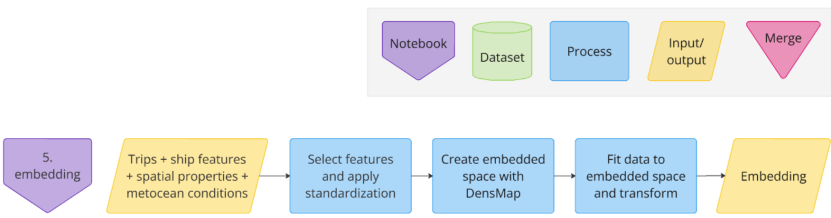

Figure 4.14: Method steps embedding with dimension reduction technique densMAP

A general requirement for many machine learning estimators is standardization of the dataset, which is done here with the *StandardScaler*. If the individual features, which are each centered and scaled independently, do not look more or less like standard normally distributed data, the machine learning estimator may be less reliable. This is why outliers have a negative impact on the balance in feature scales of the StandardScaler, as they affect the computation of the empirical mean and standard deviation. Moreover, outliers have different magnitudes on each feature, resulting in transformed data on each feature (scikit-learn developers, 2007).

For the standardization and embedding, a selection of features will be used, since not every feature is suitable for the standardization. The selected features should somewhat resemble a standard normal distribution and should not contain any Not A Number (NaN) values. With *sklearn.preprocessing.StandardScaler().fit_transform*, the selected features are standardized by removing the mean and scaling to unit variance, which results in a standard score. The following formula shows how the standard score (z) is calculated with the feature value (F), the mean (u) and the standard deviation (s) (scikit-learn developers, 2007):

$$Z = \frac{(F - u)}{s}$$

For this research, it is decided to use the StandardScalar, because it is easy to use. Not all features are Gaussian-distributed (see Appendix G), but due to time limitations, other scaling methods are not tested.

To get a reduced representation of the scaled feature data, *fit_transform* is used to fit the data into an embedded space and transform it. The UMAP constructor with densMAP parameters is used to create the embedded space (Leland McInnes, 2018). The result are trips with their specific features, represented in two feature columns, named embedding_0 and embedding_1. The values of these columns, determine the location of the points in the embedding, with embedding_0 on the horizontal axis and embedding_1 on the vertical axis. Plotting these points results in a two-dimensional embedding, with points representing trips and their distinctive features (see Figure 4.15).

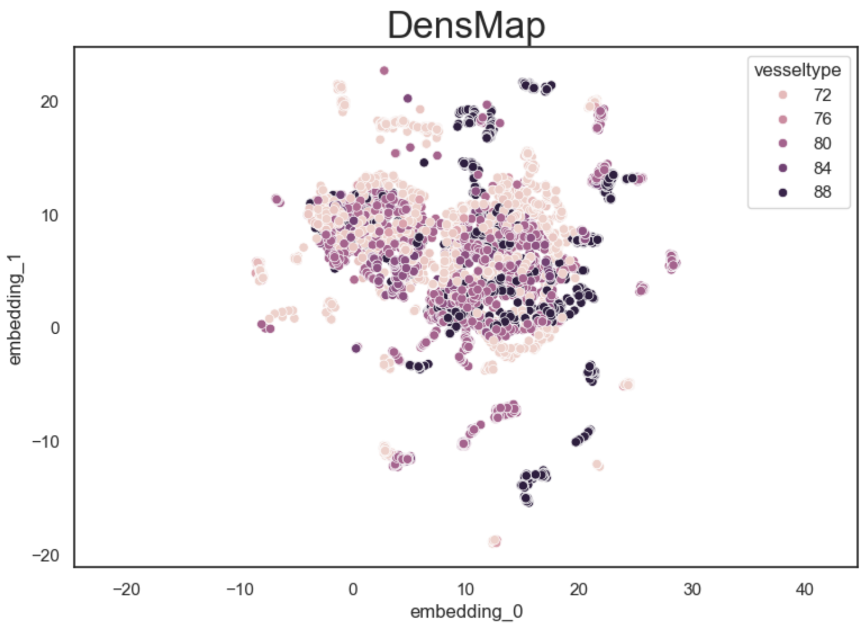

Figure 4.15: Example of embedding with densMAP

4.8. Anomaly detection - local outlier

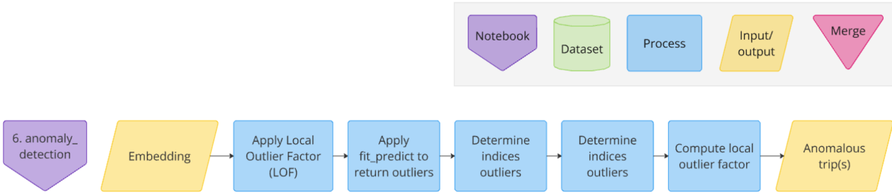

Figure 4.16: Method steps anomaly detection

To determine which trips are anomalous, the LOF algorithm is applied (see Figure 4.16). This method compares the local density of a point, in the embedding, with respect to the local density of its nearest neighbors. The distance to the k-nearest neighbors is used to estimate this local density. A point is considered as an outlier when the point has a lower density than their neighbors. In other words, the LOF score represents the anomaly score of a point, which depends on how isolated the point is with respect to the surrounding neighborhood, meaning whether the point is a local outlier.

To calculate the LOF, the number of neighbors and the contamination value are used and adjustable. Generally, the number of neighbors is set to 20, which refers to the 20 closest points to the point in question. The number of neighbors can be adjusted as desired. To be able to consider points as local outlier in relation to their group, the number of neighbors should be larger than the minimum number of points required for a group of points. The number of neighbors should be smaller than the maximum number of nearby points that could potentially be local outliers themselves. The contamination value value can be automatically set by the algorithm or manually specified (e.g. 0.01, 0.05, 0.1, corresponding to 1%, 5% and 10%, respectively). The contamination value determines the prediction errors, which are the amount of trips which are identified as outliers. In other words, the contamination value represents the percentage of the trips identified as outliers.

The *fit_predict* function uses the *sklearn.neighbors.LocalOutlierFactor* class, with the number of neighbors and contamination value, in combination with the embedding points, to return labels for the outlying points. The outlying points are labeled with a value of -1 instead of 1 for non-outlying points. The indices of these outlying points, are saved to visualize the outlier scores, and to show trajectories of these outliers (see Figure 4.18). Subsequently, the *negative_outlier_factor* function is used to determine how "outlying" the points are compared to their neighbours. All the values are negative and the lower the *negative_outlier_factor* score is, the more the point is considered an outlier. Inliers tend to have a *negative_outlier_factor* score close to -1. Circles around the outliers are plotted with a radius proportional to the outlier score (see Figure 4.17). The radius is calculated with the following formula, where X represents the outlier score (scikit-learn developers, 2024):

$$radius = \frac{max(X) - X[outlier]}{max(X) - min(X)}$$

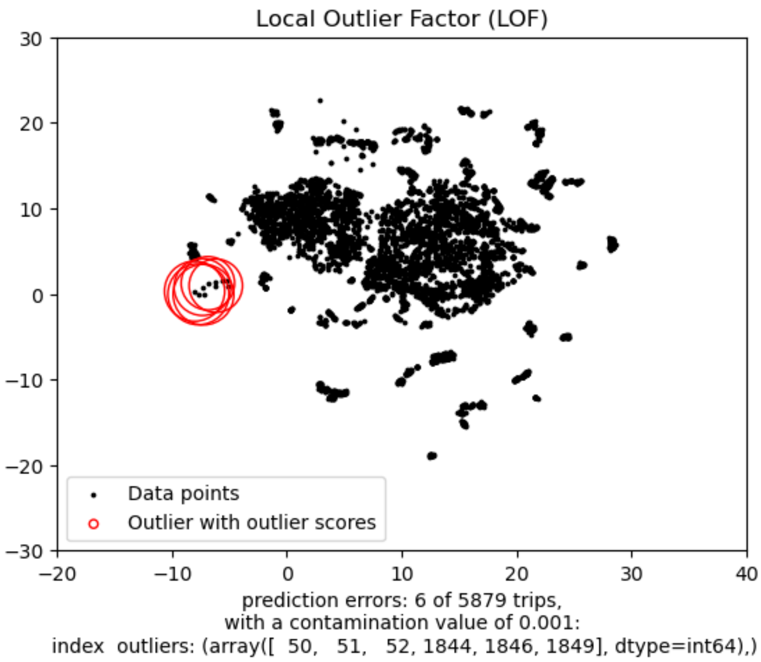

Figure 4.17: Outlier detection

4.9. Visualization

For the visualization, the coordinates of the embedding and values of the features are used. The *hvplot.scatter* function from pandas can be used to plot the embedding, in which each point represents a trip of ship. A feature can be given as a variable, which is colored according to its value relative to the maximum and minimum value of the corresponding feature of all trips. Lastly, information about a point representing a trip with its feature values can be displayed using the hover display (Holoviz contributors, 2024).

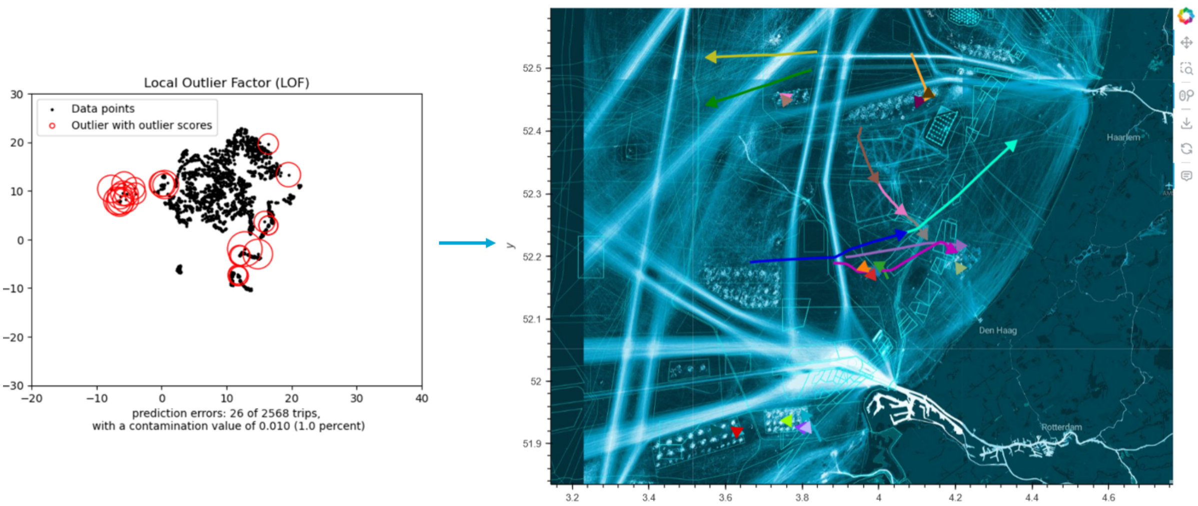

Figure 4.18: Example of the visualization, embedding with outliers and outlier trajectories

Figure 4.19: North Sea covered into multiple map tile of zoom level 8

Source: Geofabrik GmbH & OpenStreetMap Contributors (2018)

4.10. Scalability option

The detection model must predict anomalous trips within a relatively short time period (around a few seconds) across the entire North Sea. To ensure fast run time, the North sea can be divided into multiple map tile, each covering an area approximately equivalent to zoom level 8 (see Figure 4.19) (Open Geospatial Consortium, 2024). Each tile (area) will have their own trips, embedding and subsequently, outliers.

4.11. Adjustments for validation

A model has been created that can detect outliers from AIS data logs. The model filters AIS data on the North Sea and on vessel types. It then creates trips from the logs and subsequently cuts them based on a set time and duration of the trips (4.3). The trips are assigned features based on AIS data (4.4), based on where the trip travelled in space during the trip (4.5) and based on metocean conditions during the trip (4.6). An embedding with densMAP is generated based on selected features (4.7). The outliers are detected with the LOF (4.8). Subsequently, the embedding is plotted and the outliers are highlighted with a circle. In addition, the highlighted outliers are visualized by plotting the outlier trajectories for explainability (4.9). Finally, an explanation was given for the possibility of scaling up to the entire North Sea (4.10).

The results are points, representing trips, plotted on a 2D map. You expect points and clusters of points with the same features, in other words the same behaviour and behaviour influences. Then the points that are far compared to the cluster or their close neighbors are labeled as outliers. To make the 2D map and the designated outliers explainable, the trajectories are plotted with the associated features values compared to the mean of all feature values.

A few choices in the model can be used to generate results for the validation of the model. In this way, a plan can be made to produce results that answer the research questions. Specifications of the model are:

- Trips creation: Filter on North Sea and vesseltypes. Defining the one start time for trips and defining the duration of the trips.
- Feature engineering: adding motion features, spatial properties and metocean conditions.
- Embedding: Features selected from feature engineering, spatial properties and metocean conditions.
- Anomaly detection: For the comparison of different length, the contamination value and number of neighbors can be adjusted.

5

Results

To answer the research question of whether a drifting ship can be detected, a case study is applied. This case study case is about the ship the Julietta D. mentioned in the Chapter 1, which started to drift. This study will assess whether the model can detect the Julietta D. and how quickly it can do so.

5.1. Case study: Julietta D.

Marine Safety Investigation Unit (2023) investigated the incident of the bulk carrier Julietta D.,which was mentioned at the beginning of this report. The report of the Julietta D. revealed that weather conditions deteriorated around 08:00 (8:00 AM) with a wind direction turned north-west and a force of 9 Beaufort. Until 10:28 (10:28 AM), the Julietta D's movements were kept under control. At 10:30 (10:30 AM), the nearby anchored Pechora Star was informed by the Julietta D. that it was dragging its anchor. Ijmuiden Approach called Julietta D. to inquire about the situation. Around 10:42 (10:42 AM), the Netherlands Coast Guard established contact with Pechora Star regarding the an imminent collision with the drifting vessel. At 10:43 (10:43 AM) the Julietta D. made contact with the Pechora Star. The Julietta D. continued drifting southwards into the windfarm (see Figure 5.1). At around 11:19 (11:19 AM), the Julietta D made contact with a windfarm transition section under construction. At 1130 (11:30 AM), the ship appeared to drift uncontrollably instead of dragging the anchor. Afterward, crew members were evacuated by helicopter. At 14:36 (2:36 PM), the Julietta D. hit a platform under construction. The track of Julietta D. is visible in Figure 5.2.

The main conclusion is that the Julieta D. began dragging its anchor around 10:30 AM, due to bad weather conditions. Change in heading was visible compared to other ships and a reduction in SOG. In addition to the anchorage area, the vessel was present in the wind farm. The Juliettta D made contact with the Pechora Star after 13 minutes, with the windfarm transition section after 49 minutes and with the platform under construction after 4 hours and 6 minutes, after the vessel started drifting.

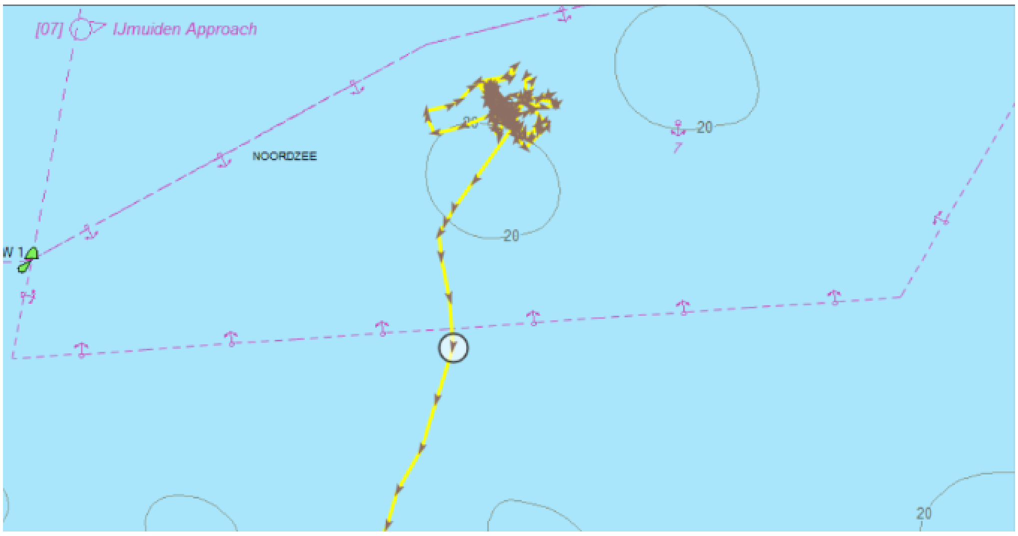

Figure 5.1: Julietta D's AIS track in anchorage area

Source: (Marine Safety Investigation Unit, 2023)

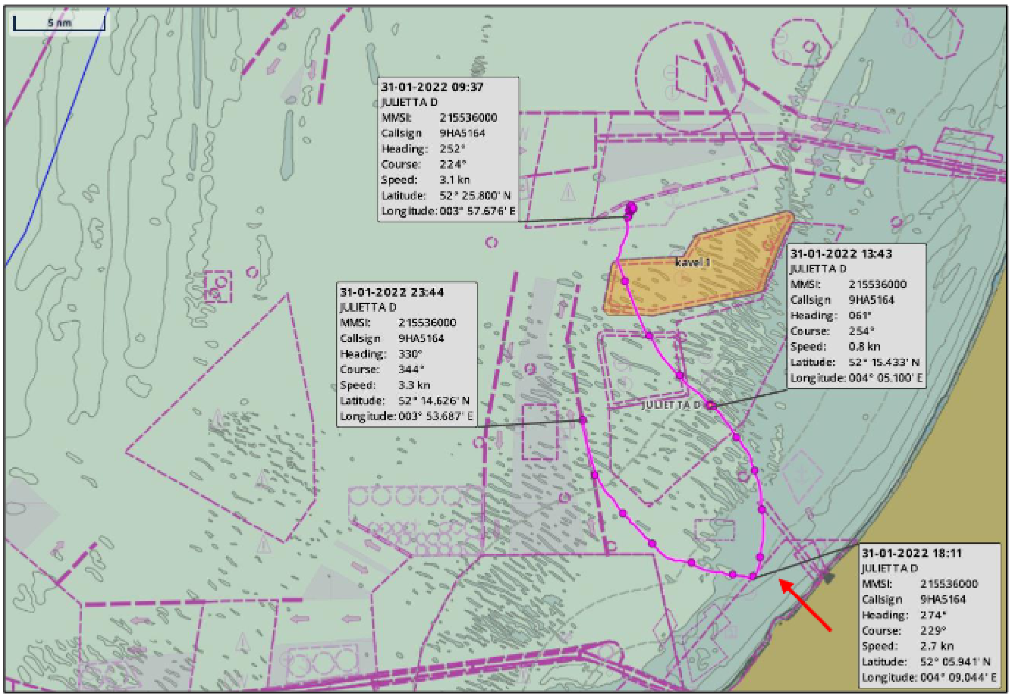

Figure 5.2: Julietta D's AIS track through windfarm

Source: (Marine Safety Investigation Unit, 2023)

5.2. AIS data

This incident occurred on February 31 and January 1 of 2022. The AIS data of cargo ships during this period, along with the relevant area where the ship was present during this period is used. For scalability, the North Sea can be divided into multiple tiles with an area approximately equivalent to zoom level 8. The tile for this case study is visible as the yellow rectangle on the left side of Figure 5.3 and covers around 570,000 hectares. It should be noted that this tile is cut off by the North Sea polygon in the model, resulting in the exclusion of ports (Rotterdam and IJmuiden) and inland waters from this area. The corresponding trips, from AIS data in this period and area, are visible in the right side of Figure 5.3. Trajectories are plotted to show the geo-spatial behaviour of ships (sub-question 4).

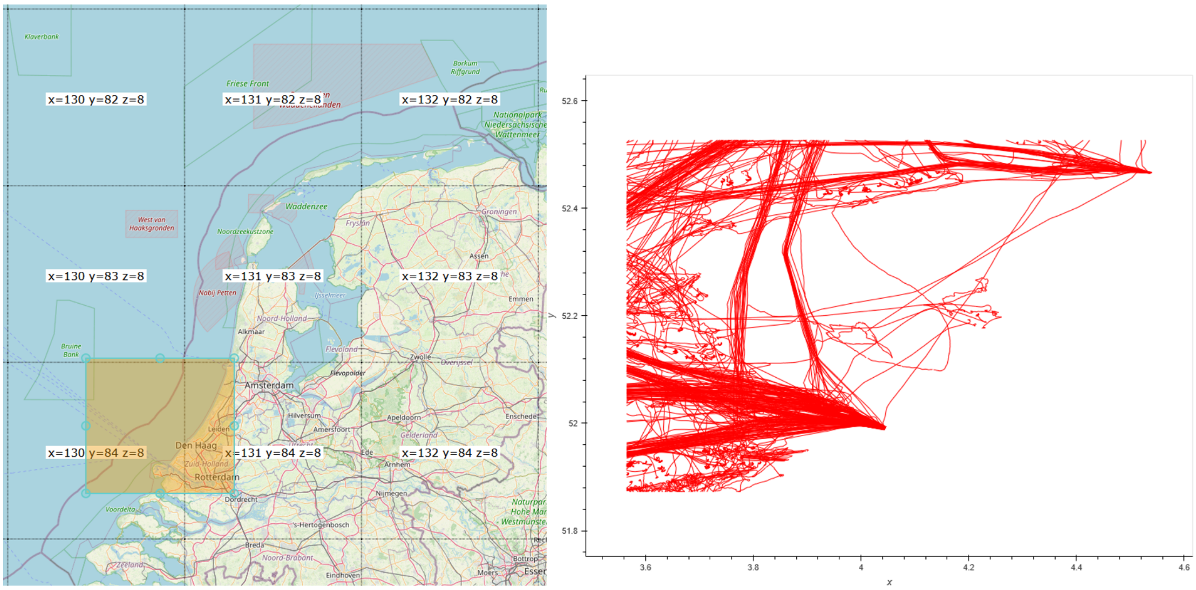

Figure 5.3: Case study area as tile (yellow rectangle area with blue outline in left figure), including ports and inland waters, and the trajectories within this tile and the North Sea (right figure). The x-axis corresponds with the longitude values and the y-axis corresponds with the latitude values

Source: Geofabrik GmbH & OpenStreetMap Contributors (2018)

5.3. Embedding

First, trajectories of a duration of 60 minutes are made from the AIS data, starting at 8:30 AM on 31 February 2022. Other trips that do not fall within the 8:30 - 930 AM time frame begin with a start time of 8:30 AM minus or plus (a multiple) of 1 hour (e.g. 830 AM - 3x1h: 5:30AM). This time (8:30 AM on 31 February 2022) was chosen because Julietta D. started drifting at that moment. This allows for determining how quickly the ship is detected. Features are generated (see left side Figure 5.4). With densMAP a two dimensional embedding is generated with each point representing a trip with corresponding features (see right side Figure 5.4). The trips are plotted relative to each other based on their features. One trip in the embedding (see red dot in left side of Figure 5.5) represents a trip of 60 minutes, this trip is plotted in the right side of Figure 5.5. By plotting the point in the embedding as a trajectory on a map of the area on the North Sea, the embedding is easier to understand (explainabe). Groups of samples can be visualized by means of plotting groups of points and their corresponding trajectories. The left side of Figure 5.6 shows a selection of points on the the embedding, representing a group of trips (right side). This group of trips represent vessels present in the approach areas of the ports IJmuiden and Rotterdam (the right side of Figure 5.6). The left side of Figure 5.7 shows a selection of trips on the bottom of the embedding. If you plot these trips, a group of anchored vessels are visible (see right side of Figure 5.7).

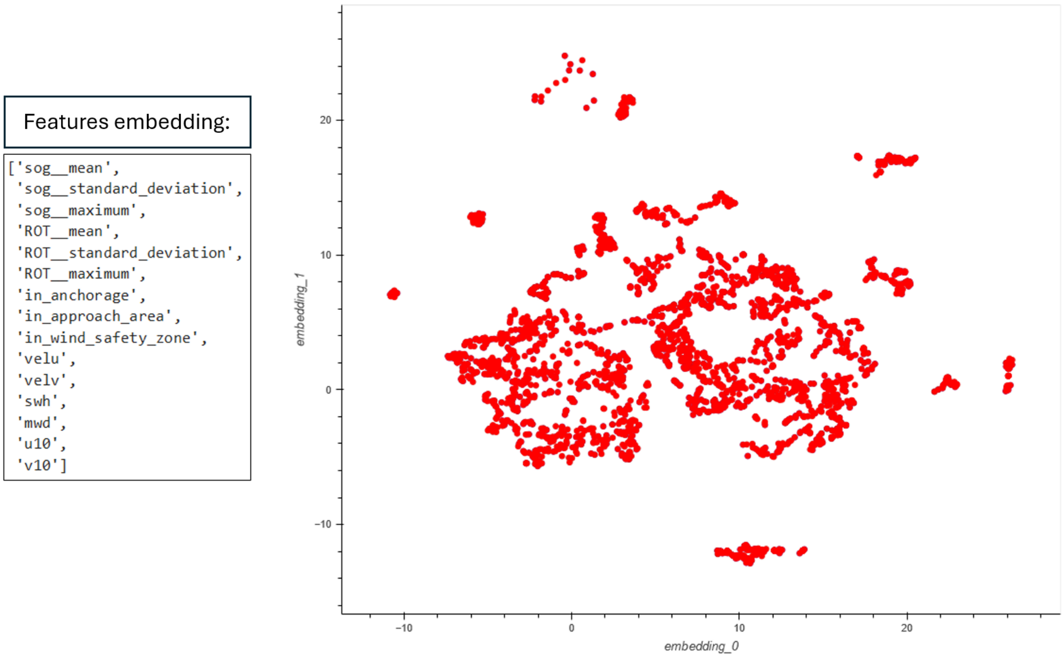

Figure 5.4: Trips of 60 min in embedding, total of 2974 trips, with corresponding features

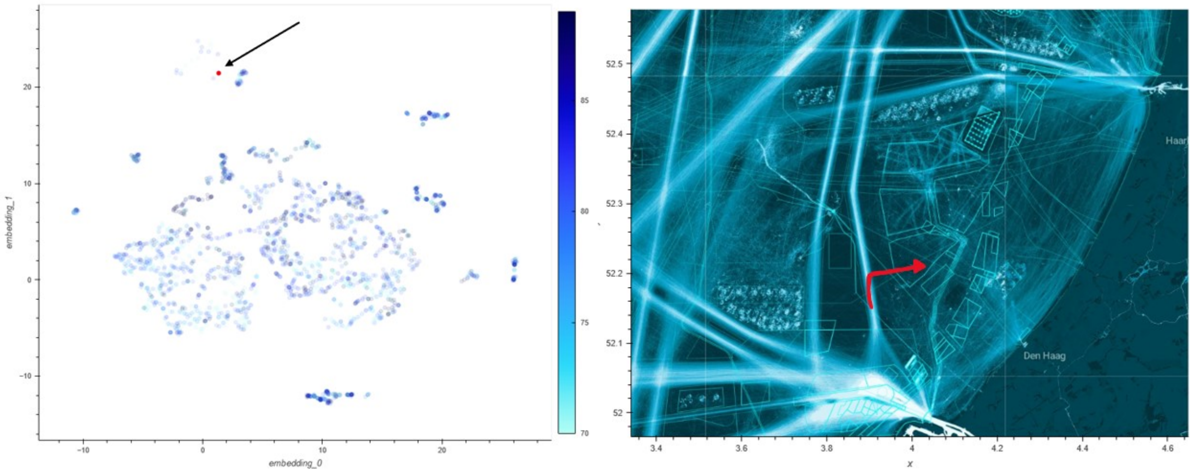

Figure 5.5: One selected trip of 60 minutes in the embedding (red point in the top, left figure) with its corresponding trajectory (blue arrow, right figure)

5.4. Anomaly detection, local outlier

The outliers will be detected with a function using the LOF. For this function different settings are possible, namely the number of neighbours and the contamination value. The number of neighbours is kept on 20, which is the default value of the function. The contamination value, which describes the percentage of the trips that should be detected as outlier, is deviated from 0.001 (0.1%) to 0.05 (5%). In Figure 5.8 (left side) the outlier factor is computed for a contamination value of 1% . The corresponding trajectories are plotted in the right side of Figure 5.8. It can be observed in the figure that the Julietta D. is already visible (a series of arrows pointing south).

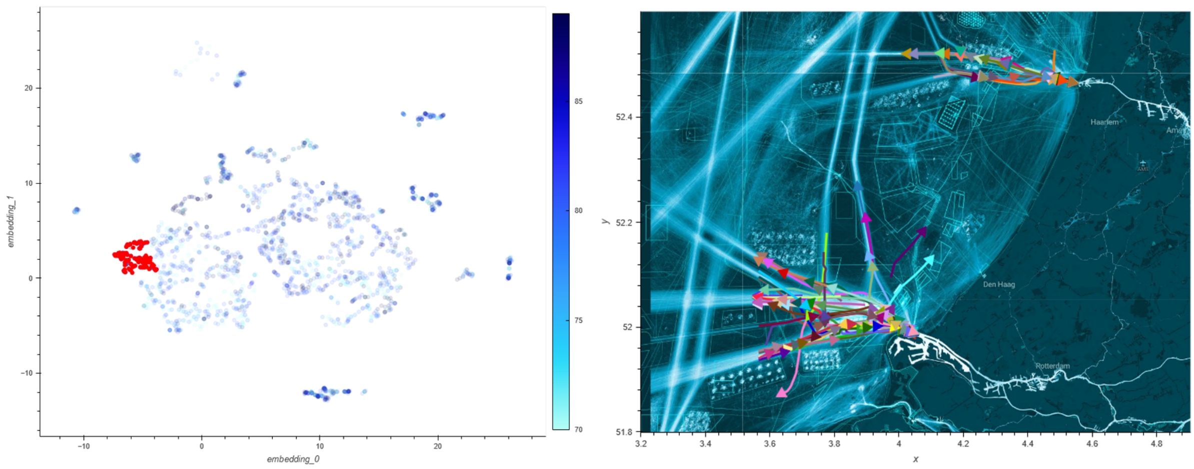

Figure 5.6: Groups of points in embedding (left) and their corresponding trajectories of 60 minutes (right) - vessels in approach areas

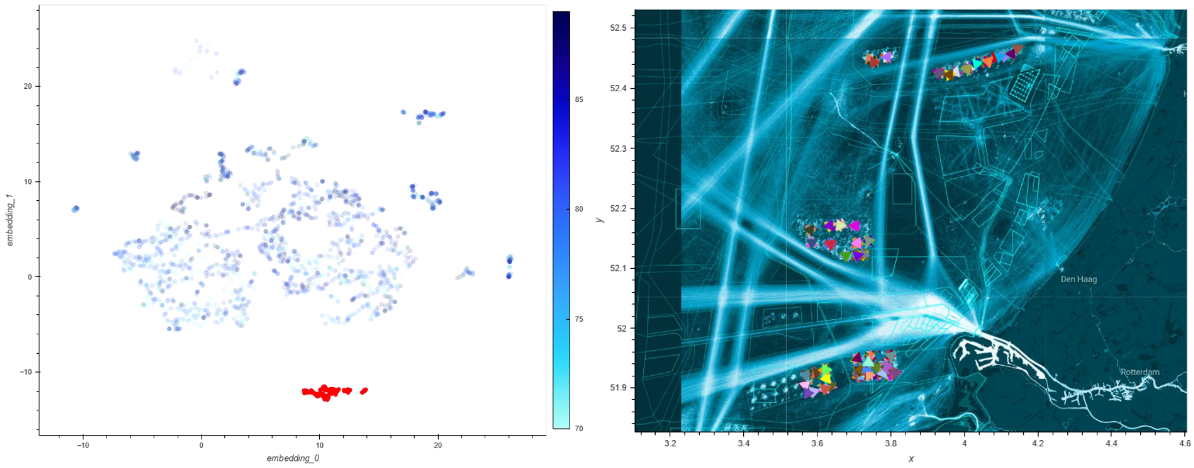

Figure 5.7: Groups of points in embedding (left) and their corresponding trajectories of 60 minutes (right) - anchored vessels

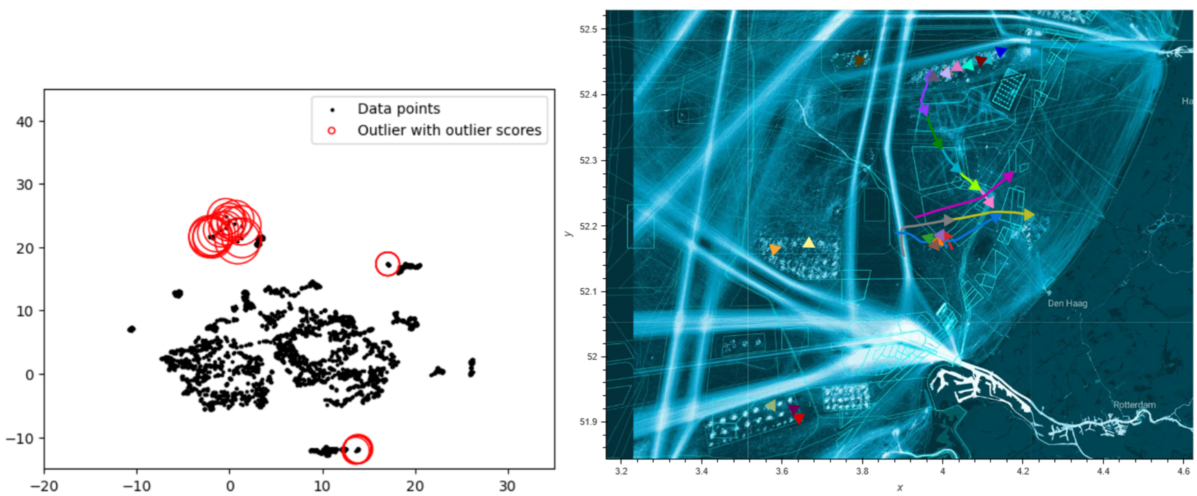

Figure 5.8: Local outlier of 1 percent of 60 min trips (, namely emb30. left figure) and corresponding trips (right figure)

5.5. Detecting Julietta D.

In this section the speed of the detection of Julietta D. is tested, which is important to determine the operability of the model (sub-question 5). Trips of one hour was applied in the previous section. For this duration, the Julietta D. was faster detected than the 4 hours and 6 minutes it took the vessel to reach the platform under construction. A trip that is faster detected than 1 hour shows improvement of the current detection speed of the ship. The goal is to detect the Julietta D. faster than the time it took the vessel to reach the wind farm transition section (49 minutes). To be able to do this, the trips are cut in 30 minutes with a set fixed time to be able to compare the speed of the detection. The start time is set with the time when the Julietta D. started drifting. In addition, different features (and feature combinations) are tested. When the same features as Figure 5.4 are used for a trip duration of 30 minutes, a contamination value of 1% (and 5.5%) and 20 neighbours, the Julietta D. is not detected. For the embedding (emb32) with trips of 30 minutes, the total amount of trips is 2974, with 5.5% outliers, this results in 256 outliers.

New features were added and a new embedding was generated (emb33). With a contamination value of 1% the Julietta D. was detected. A total of 47 trips were detected as outliers in which nine trips belonged to the Julietta D (see Figure 5.9 with the arrows from north to south-east: purple, orange, brown,.. ,light purple and light green in the figure).

The following features were used for the detection (embedding33):

- Ship features: sog [mean, standard deviation, maximum, minimum, 10% quantile, median, 90% quantile and skewness], ROT [mean, standard deviation, maximum, minimum, 10% quantile, median, 90% quantile and skewness] and length to beam ratio;
- Spatial properties: in acnhorage area, in approach area, in safety zone wind park and crossing the TSS;
- Metocean conditions: velu, velv, swh, mwd, u10 and v10.

Table 5.1 shows the settings applied for the detection of Julietta D. (for embedding 33).

Table 5.1: Model settings, detection Julietta D.

Model step	Setting
Trips creation	Filter cargo ships
	Start time trips: 8:30 AM on 31 February 2022
	Trip duration: 30 minutes
Anomaly detection	Contamination value: 1 % and n = 20

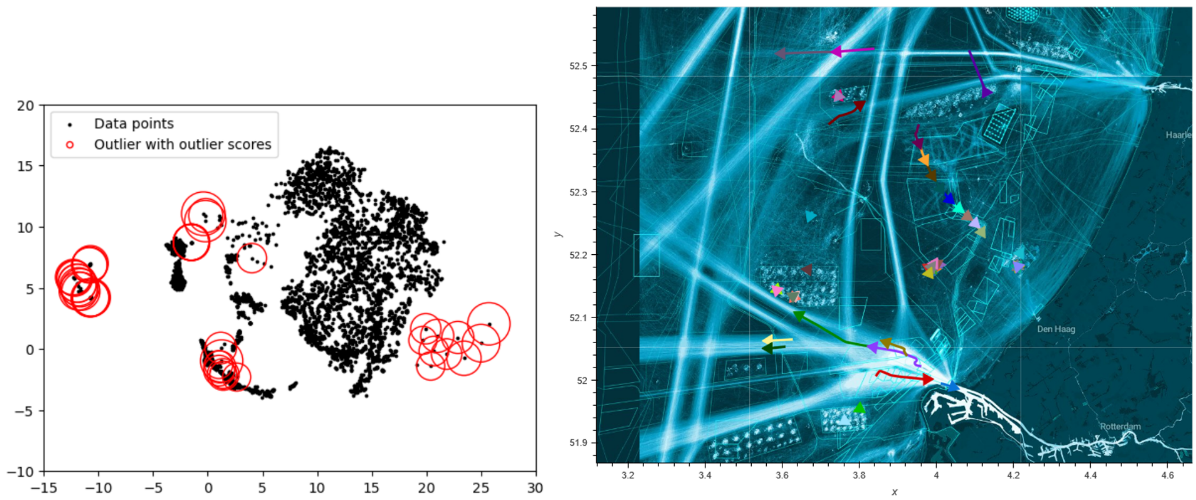

Figure 5.9: Julietta D. detected with 30 min trips and 1% contamination value (embedding 33)

Now we can check which trips belong to the Julietta D., by plotting a selection (group of trips) at the left side of the embedding, we can show the feature importance and the trajectories of the group (see Figure 5.10, 5.11, 5.12). The feature importance is represented as a bar for each feature. The average value of the feature for the selected trips are comparable to the the average value of that feature of all the trips. Figure 5.11 shows the deviation of the average feature value for the group (Julietta D.'s trips) compared to the average value of all trips of the following features: maximum of ROT and 90% quantile of ROT.

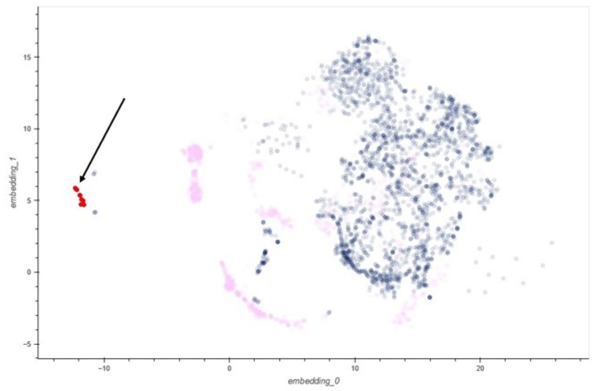

Figure 5.10: Julietta D. plotted by selection in embedding: the selected group in the embedding

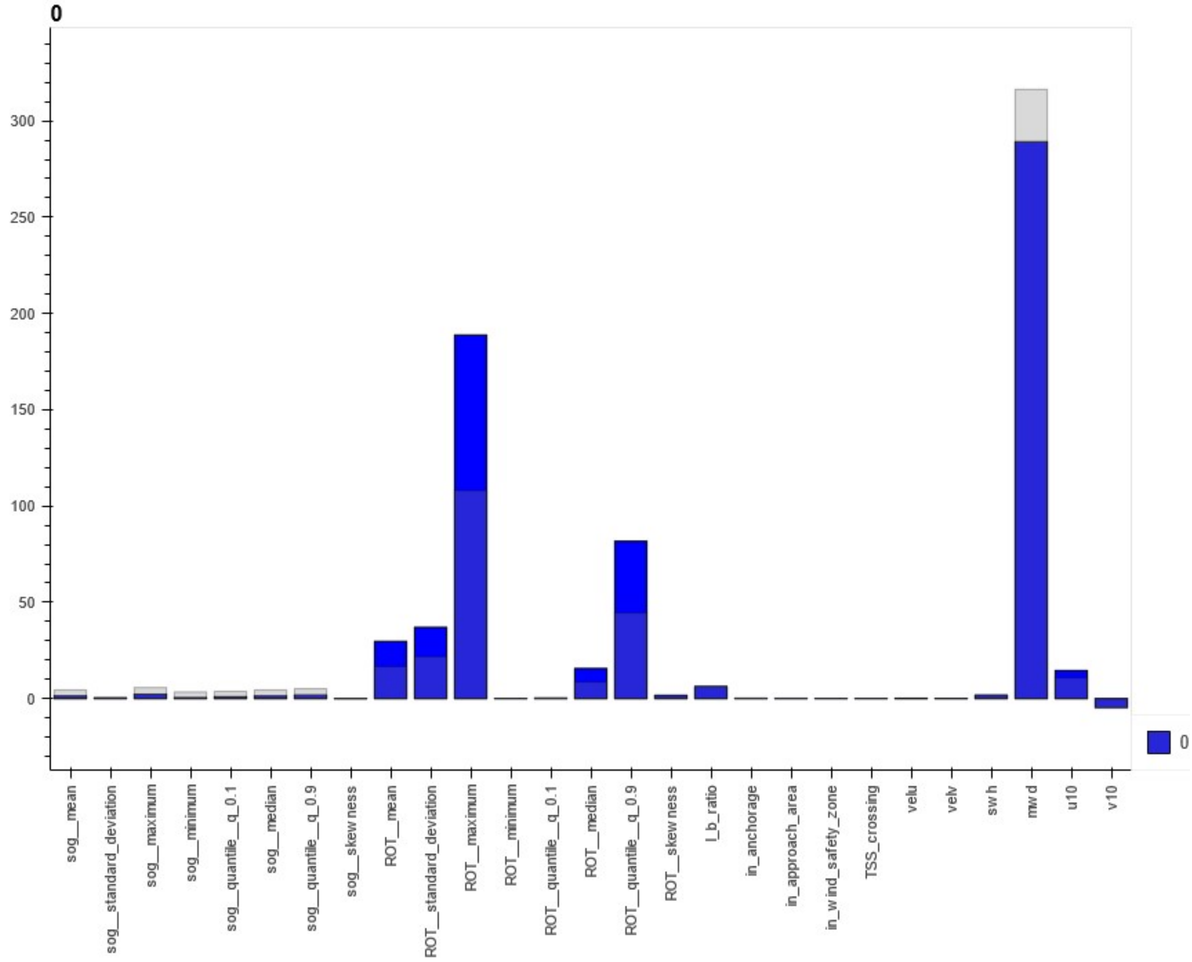

Figure 5.11: Julietta D. plotted by selection in embedding: feature importance of the group

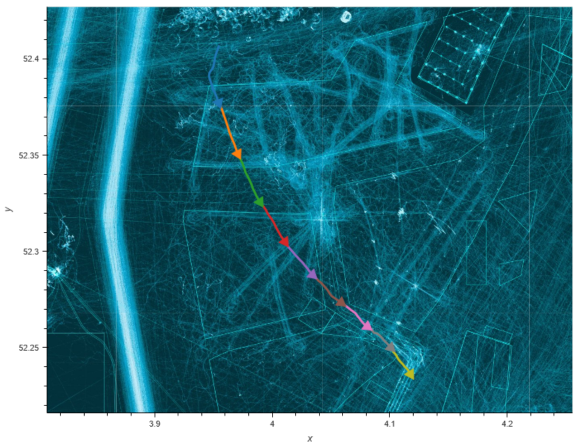

Figure 5.12: Julietta D. plotted by selection in embedding: trajectories

5.6. Detectable types of behaviour

The drifting ship Julietta D. is successfully detected with the model (see Figure 5.9). This model can also detect if a ship crosses an area, but does not yet know when the ship is in or out of an area (see Figure 5.6). In addition, the model detects sudden changes of speed of a ship trajectory (see Appendix H). Finally, the ship detects ships at anchorage outside the port (see Figure 5.7). The sudden change in heading and present in an area in a certain time of the day are not yet possible to detect, since the heading is not used as feature and the time component is not used as feature. The behaviour types spoofing position and not reporting are outside of the scope of the project. The remaining types of behaviour, namely ship at port at sea, encounter at sea, heading to/ off shore and distance to shore is not detected. Reasons for this are: the port areas are outside the scope of this research (ship at port at sea), ship encounters are not taken into account as feature (encounter at sea) and the area of the North Sea does not include the shore, the distance to the shore and the heading (heading to/ off shore and distance to shore). An overview of the detectable behaviour types is visible in Figure 5.13).

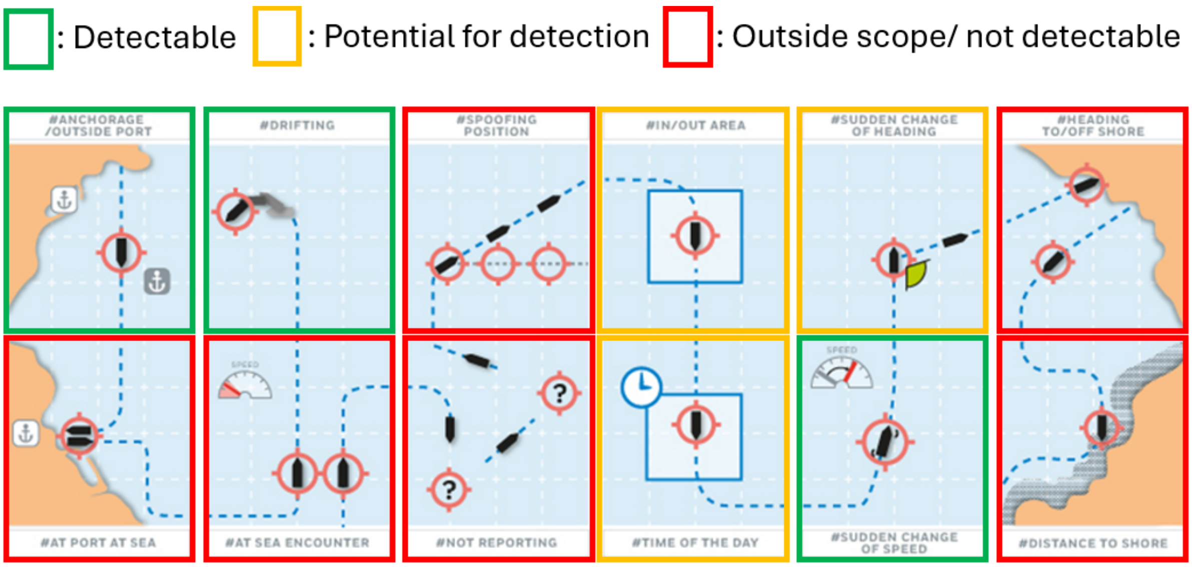

Figure 5.13: Behaviour types possible to detect with model (added from source)

Source: European Maritime Safety Agency (2024)

6 Discussion, Conclusions and Recommendations

In this research, relevant information was gathered, and a model was developed to detect anomalies in AIS data on the North Sea. This chapter presents the discussion, conclusions and recommendations of this research. The discussion includes the research relevance, comparison with previous work and limitations of this research. Subsequently, the answers to the sub-questions and main research question are described. And finally recommendations for future work are done.

6.1. Research relevance

The model has potential for the Coast Guard, because multiple features can be added, its applicable to an operational setting for both safety and security purposes, warnings can be issued, or vessels displaying anomalous behaviour can be highlighted, the detection can be used for training purposes to better understand characteristics of anomalous behaviour, historical data can be analysed and new types of behaviour may emerge, as the method is non-rule based, and historical events of a limited time period may be analysed.

The potential for research consists of: having found the intersection/ balance between rule-based tasks for people in practice (in operational settings) and deriving rules from data. This provides an opportunity to bring together and facilitate collaboration between professionals (skilled workers) and data analysts. Unknown anomalous behaviour that has not yet been identified may be discovered, the current rules are being challenged as behaviours can be expressed in features, e.g. from knowledge of practice, instead of rules in codes. Through automation, practice and research can be integrated; however, the people in practice must be involved in the developments to ensure that automation does not feel imposed.

6.2. Comparison with previous work

The proposed method by van Engelen (2023) applied to AIS data from inland waters to generate clusters of similar behaviour, provided a solid foundation for this research aimed at detecting anomalies at the North Sea. Compared to this method, the current model is applied to cargo vessels in the North Sea, incorporating different features such as spatial properties and metocean conditions. DensMap was utilized instead of UMAP, and anomaly detection was employed instead of a clustering technique.

An example of anomaly detection in a field outside of maritime, is the research of Weijler et al. (2022). Which used UMAP in combination with HDBSCAN and partly labeled data as one-class classification approach for the detection of blast clusters, what can be described as anomalies. While UMAP and HDBSCAN could serve as viable alternatives for clustering behaviour types, the one-class classification approach is not suitable for this research, which requires a multi-class classification framework for multiple types of anomalous behaviours. In addition, no labeled data were available for this research, so the anomaly detection should be unsupervised. In conclusion, a mutli-class classification utilizing UMAP and HDBSCAN, combined with labeled data of anomalous behaviour types, has the potential to detect anomalous behaviours, specifically global anomalies. This limits anomalous behaviour types to the availability of labeled datasets, meaning that new behaviours may go unnoticed.

Monitoring and detecting abnormal ship behaviour can be based on rules, like the ABM model which uses data from several tracking systems (European Maritime Safety Agency, 2024). Rong et al. (2024) is an example of a rule based approach, in combination with AIS data, for detecting and classifying ship abnormal behaviour in ship trajectories utilizing KDE, DBSCAN and RF. This approach uses statistical analysis to identify anomalies. Ship abnormal behaviour can be analysed with motion parameters (speed, COG and lateral distance) of ship trajectories and characterizing ship abnormal behaviour types by motion features . The method of Rong et al. (2024) identifies abnormal initiation points and differentiates the time intervals of ship abnormal behaviour, resulting in an improvement of features by capturing the abnormal behaviour. The following features were proposed: standard deviation of the speed, detour factor, maximum drift angle, accumulative COG change, delta COG, maximum lateral distance. Compared to this research, features are generated over a set time duration, independent of the occurrence in time of anomalous behaviour, which make the ship features in this report less accurate, since the features can be a result of a mix of normal and anomalous behaviour. On the other hand, this method of Rong et al. (2024) does not include environmental conditions and the locations with its context where the ship is sailing. The method does include deviations from the route of the itinerary, which is missing in this research. The method of Rong et al. (2024) is suitable for identifying and classifying four predefined abnormal behaviour types namely, circular, U-turn, Double U-turn and off-road, for specific ship routes. The disadvantage is that this requires AIS data from complete ship's routes, and routes that occur very rarely are not reflected in the detection model. Furthermore, the question is whether the four types of abnormal ship behaviour cover all anomalous behaviours, including new ones, which are initially based on the speed, direction, and lateral distribution. Rong et al. (2024), used statistical analysis to identify anomalies using pre-defined statistical threshold from underlying distributions. This statistical-based method does not accurately capture relationships between features, whereas this research can capture these relations.

6.3. Limitations

General limitations are divided into limitations of materials, methodology (approach, method and model steps), validation and operational setting and into external factors. The main limitations of this research are missing of the heading information, as this proved to be a key feature of the Julietta D. At the moment, the Julietta D. is anomalous, because the ship was in the safety zone of the wind farm, while this is not a defining aspect of a drifting ship, the heading is. Currently, the time component is not taken into account as feature, meaning it is unknown whether a ship is sailing in the night or during the day. In addition, this detection method is suitable for local outliers and not for global outliers.

Materials limitations: Manually entered statistical information, like ship dimensions, ship type, navigational status, destination, ETA and MMSI number, contain inaccurate or incomplete data. Dynamical information regarding the heading is not always complete. In addition, quality issues of AIS data are caused by sensor reliability, radio signals interference and wrong intentions (like spoofing and manipulation). These inaccuracies can lead to incorrect detection of anomalous behaviour or false positives when applied in the detetion method.

Methodological limitations, approach of area: The North Sea polygon is used to define the boundaries of the North Sea, and similar boundaries are established for the individual tiles covering the North Sea. However, this approach can result in the loss of information at the edges of these polygon and tiles, particularly when trips are cut off at these boundaries. To facilitate meaningful comparisons between trips, it is essential that each trip exhibits the same specified duration, for example 30 minutes, and that the entire trip is assigned to a tile without being truncated at the boundaries. Currently, this aspect is not addressed in the methodological approach.

Methodological limitations, approach of outlier: In Chapter 3 a distinction was made between noise and an anomaly, this distinction is not made in the model. In addition, this Chapter described the difference between local and global outliers. The function for detecting the outliers is currently based on local outliers and will not detect global outliers, i.e. clusters of trips that are anomalous. When all vesseltypes are included or a longer duration of AIS data is applied, clusters of trips are expected to be present, instead of one cluster. With an embedding consisting of multiple clusters a detection method for global outliers should be applied

Methodological limitations, method: Generated features should be suitable for standardization. For example, vessel type groups could be added based on a binary classification (i.e., whether a vessel belongs to a specific group or not) instead of relying solely on the vessel type codes as a feature. Additionally, the weights of features in the model (detection) are not accessible. While some features or combinations of features may hold more importance than others, their influence cannot be adjusted. For the dimension reduction technique, DensMap is chosen, because it takes local and global structure of the data into account (Mcinnes et al., 2020). This means that DensMap may not be the best option for embeddings with only one cluster, which primarily has a local structure. The LOF, used for outlier detection, is based on the contamination value and the amount of neighbours. The contamination value is predefined, instead of deviating according to the amount of anomalous behaviours. An example of this is an expected rise in outliers, thus a higher contamination value, in case of difficult metocean conditions or high traffic density. The amount of neighbors can be adjusted manually, this means the amount of neighbors is not set for optimum result according to the amount of trips. The variation of the amount of neighbours is expected to be dependent on the amount of points in the embedding and clusters in this research this aspect is not investigated. For now the LOF only takes into account local density of the 20 neighbors and not the local density of all the data. In addition, the method StandardScalar was used, which is sensitive to outliers and therefore cannot guarantee balanced feature scales (scikit-learn developers, 2024). Finally, the impact of the number of features and the influence of individual features on detection have not been thoroughly tested.

Methodological limitations, model steps: In the model, the trips belonging to the same ship, are not coupled. Due to splitting of trip based on a defined duration, there is potential loss of information at the time of the split. Furthermore, a combination of trips may appear anomalous, even if separate trips does not. In addition, the extra information obtained from longer trip durations can result in the detection of different anomalies. For instance, longer trip durations provide more AIS data logs, which can enable the creation of new or enhanced features (e.g. kurtosis which needs at least 4 values). In the method step for generating ship motion features, data with NaN values for skewness, which requires at least three values, are excluded. In Chapter 2, factors which can be implemented as features, influencing sailing behaviour were mentioned. Not all features have been incorporated, and factors such as traffic density or interaction with other vessels can be of importance. Currently, the model focuses on geospatial behaviour rather than geospatial-temporal behaviour, as the component has not yet been integrated (as a feature). For these two days, the time component is not expected to have a significant impact. The TSS is currently unsuitable to use as spatial property, because the lines do not close, and the TSS geometry is not yet represented as polygon. Additionally, the spatial properties of the North Sea are not yet complete, as the infrastructure (such as buoys) is not fully implemented.

Validation limitations: The test case covered two days and cargo ships, meaning a limited number of trips, a limited variation in metocean conditions, and a selected group of vesseltypes. In addition, the model is not tested on multiple tiles on the North Sea, only one. This means the accuracy and scalability has not been (properly) tested.

External factors: The introduction of this research mentioned that the North Sea will see an increasing number of wind turbines in the coming years, as it has in recent year. This development, along with several others developments, leads to a challenging factor for the model, specifically spatial properties, as the spatial arrangement of the North Sea changes over time.

Operational limitations: Over time, new anomalous behaviours can emerge. This model is well-suited for identifying and potentially detecting these additional behaviours. The outliers detected by the model are not necessarily considered anomalous or unsafe from the operator's perspective. The model misses additional information about developments in the present time, for example, temporary permits for ships in defined areas.

6.4. Conclusions

This paragraph will address the sub-questions, leading to the answer of the main research question.

Sub-question 1

”How are incidents and anomalous ship behaviour types currently regarded, how does the Coast Guard focus on these safety concerning behaviours, and what requirements should a detection model meet to enhance monitoring in the operational setting?”

Marine casualties and incidents were mentioned, in which marine casualties can be described as incidents with damage as a consequence. In the EMCIP model in European Maritime Safety Agency (2023), casualty events are divided into occurrence with ship(s) and occurrence with person(s). The classification for the occurrence with ships is: capsizing/ listing, contact, fire/explosion, grounding/ stranding, loss of control, collision, damage/ loss of equipment, flooding/ foundering, hull failure and missing. The classification of anomalous ship behaviour types are mentioned, namely: anchorage outside the port, drifting, spoofing position, entering an area of interest, sudden change of heading, approaches to shore, ship/ activity at port at sea, ship encounters, not reporting, ship in area at certain time of the day, sudden change of speed and distance to shore (European Maritime Safety Agency, 2024). The Coast Guard focuses on the safety concerning behaviour by combining multiple sources of information to gain a clear understanding of the current maritime safety situation on the North Sea. They carry out the monitoring tasks by using screens, communication tools (e.g. reports of skippers) and intelligence. Experience and context influence the assessment of ship behaviour. Requirements of the detection model, to enhance monitoring with respect to operational use, are: gradual implementation of the model, the model should instill confidence, be interpretable, be easily explainable, the detection should be fast and accurate and the number of (detection) alarms should be limited. Requirements with respect to application in an operational setting are: a user friendly interface, capable of real-time processing, scalability and capable of integration with other data sources and rules.

Sub-question 2

”What are contributing factors to safety concerning behaviour, and what anomalous behaviour should be detected?”

Factors influencing the sailing behaviour are:

- external environment regarding metocean conditions: wind, currents, tide, temperature (fog and hydrodynamic effect);
- visibility: time of day, fog, high traffic density;
- external environment regarding vessel interaction: passing vessels that influence hydrodynamic effects/ environmental dynamics and influence the decision-making process;
- limited maneuverability of the ship: dependent on infrastructure, bathymetry and position of other vessels (related to traffic density)
- influences traffic density: time of day, location and season;
- voyage: sailing or anchoring in spatial areas, route bound and non-route bound traffic (TSS).

To distinguish between different anomalous behaviours, the classification of anomalous ship behaviour types from the ABM of European Maritime Safety Agency (2024) is used. The anomalous behaviour that was selected for detection, is drifting. Comparing the behaviour type drifting to the classification of casualty events in the EMCIP model, this behaviour has similarities with the class loss of control.

Sub-question 3

”Which machine learning approaches and methods have a great potential to enhance operational tools for detecting anomalies?”

The machine learning approach, which has a great potential for detecting anomalies, is an unsupervised, density-based method. The approach involves the use of characterizing features for each trip of a vessel, combined with a dimension reduction technique and an outlier detection method. For the dimension reduction technique, densMAP was selected and for the outlier detection technique the LOF was used. This dimension reduction method was chosen because of the good performance and ability to preserve the density of the data. The LOF was chosen, because it was density-based and the function was already implemented in Python.

Sub-question 4

”How can the geospatial-temporal behaviour of a ship, along with its contributing behavioral factors, be integrated into a model utilizing the selected machine learning approach and methods to effectively detect anomalies?”

Geospatial-temporal behaviour of a ship, along with the contributing behavioral factors, can be integrated into the model using features. AIS data logs were used to generate trajectories per ship, with a defined duration. For each trip features were generated, representing the ship motion and the influencing factors of behaviour. Features that were selected to detect the anomalous behaviour drifting, are the mean, standard deviation, maximum, minimum, 10% quantile, median, 90% quantile and skewness of the SOG and ROT values, in addition the length to beam ratio was used. Furthermore, the location where the ship has been during the voyage has been taken into account as spatial properties. Theses spatial properties consisted of information about whether the ship crossed the anchorage area, approach area, wind safety zone and TSS. As a final feature, metocean conditions have been added, namely velu, velv, swh, mwd, u10 and v10. Which represent the eastward- and northward component of the velocity, the significant wave height of combined wind waves and swell, mean wave direction and eastward- and westward component of the wind speed at 10 meters above the surface respectively. Trips, with its characterizing features, are plotted as points on a two dimensional embedding using DensMap. Trips with similar features are expected to be plotted close to each other. After the points are plotted the LOF is used to determine the local outliers, the lower the LOF value, the more the point is seen as an outlier. The LOF is determined based on the number of closest neighbors, which is set to 20, and the contamination value, which can be adjusted. The contamination value determines what percentage of the total number of points/ trips is labeled as an outlier.

Sub-question 5

”Can the selected anomalous behaviour be detected by the model, what is the detection speed, and does the model have the potential to detect other types of anomalous behaviour?””

To test if the model can detect the selected anomalous behaviour, a case study has been conducted. A combination of features, trip duration and model setting determines the accuracy of the detection. The case study was about the drifting ship Julietta D.. AIS data of 2 days in 2022 were used when the drifting occurred as well as the concerned area of the North Sea. A filter for cargo ships was applied and the trip duration was set to 30 minutes. The following features were selected to detect the Julietta D.: mean, standard deviation, maximum, minimum, 10% quantile, median, 90% quantile and skewness of the SOG and ROT values, in addition the length to beam ratio, spatial properties (crossing anchorage area, approach area, wind safety zone and TSS) and metocean conditions (velu, velv, swh, mwd, u10 and v10). The number of neighbors was set to 20 and the contamination value was set to 1%. This resulted in the model successfully detecting the Julietta D in the aforementioned AIS data set. To check the speed of the detection the trip duration was adjustable as well as the ’start’ time of the trajectories. This start time was set as the time the Julietta D. started drifting, namely 10:30 AM. To be able to determine the detection speed of the Julietta D., the model should detect the first 30 minutes of the drifting trajectory, and it successfully did so. It can now be concluded that the ship was detected in 30 minutes, which is faster than the time it took the Julietta D. from the start of the drift to hitting the platform under construction (after 4 hours and 6 minutes) and the windfarm transition section (after 49 minutes). Finally, to determine if the model has potential to detect other types of anomalous behaviour, trajectories of different clusters of points in the embedding were plotted. The model can detect drifting vessels, if the vessel is anchored outside the port, and if a vessel displays a sudden change of speed. In addition, the model has potential to detect if a vessel is in a specified area, if a vessel displays sudden change of heading and if a vessel is present at a location at a certain time of the day. In these cases, features like heading, presence of the trajectory in a specified area and a time component should be added as features. An overview of the possibility to detect different types of behaviour was made.

Research question

"How can machine learning enable operators to detect anomalous cargo vessel behaviour with potential safety implications, on the North Sea, more quickly, validated against historical data from a known incident?"

To enable operators to detect anomalous cargo vessel behaviour, with potential safety implications, more quickly, a detection model for unsupervised AIS data was developed. The goal of the detection model is to highlight vessels exhibiting anomalous behaviour, specifically drifters, in order to support the Coast Guard. This model showed that detection of the drifting ship Julietta D. was successful and possible within 30 minutes, while the time between the vessel drifting and the vessel making contact with the wind farm transition section under construction, was 49 minutes. This model showed potential to detect more anomalous behaviour types by improving features, adjusting trip durations and model settings.

Regarding the requirement of the detection model with respect to operational use:

- detection should be fast: could detect a vessel in 30 minutes.
- be easily explainable (EML): the points in the embedding were visualized as trajectories on the North Sea.
- instill confidence: plotting the trajectories of groups in the embedding, revealed vessels exhibiting similar behaviour.
- be interpretable: the feature importance of the groups was visualized.
- detection should be accurate: the Julietta D. was detected, but false positives and false negatives were not tested.
- number of alarms should be limited and gradual implementation of the model: outside the scope of this research.

Regarding the requirement of the detection model with respect to operational use:

- scalability: the model has the possibility to cover the entire North Sea while maintaining a fast run-time by dividing the area into multiple tiles, each their own trips, embedding and outlier detection. The run-time for creating the embedding was 16 seconds and the run-time for the outlier detection a few seconds. The features can be computed parallel.
- capable of integration with other data sources and rule: the metocean conditions and locations of areas on the North Sea were integrated into the model.
- capable of real-time processing: the model has the possibility for real-time processing, provided that the embeddings for the North Sea tiles have already been created. New trips can be added to the embedding over time.
- a user friendly interface: this was outside the scope of the research.

6.5. Future research

General recommendations for future research are divided into recommendations of materials, methodology (approach, method and model steps), validation and operational setting. The main recommendations for enhancement of the model is to add the heading and a time component as a feature and incorporate a global outlier detection method. Furthermore, test and improve the model with a labeled dataset and validate the model with publicly available AIS data.

Materials recommendations: IVSnext and Lloyds Register can enhance the accuracy of ship dimension information, such as lenght, width, height and draught. Additionally, IVS includes data on the weight of cargoes carried by vessels. However, there are limitations due to the need to comply with the General Data Protection Regulation (GDPR) (Zagonjolli et al., 2024).

Methodological recommendations, approach and method: For future research, it is recommended to utilize labeled datasets of known incidents to verify the detection method and to identify features associated with different types of behaviour. This shift from unsupervised to a supervised machine learning approach will enhance the detection of known behaviour types. In the embedding clusters can be identified using techniques such as DBSCAN. Subsequently, SHAP can be applied to assess feature importance within each cluster (Rong et al., 2024). Finally, local outliers and global outliers can be detected. By improving these features, the accuracy of identifying behaviour types and consequently the accuracy of detecting anomalous behaviour types can be significantly enhanced. Furthermore, the methodology can be expanded from merely detecting anomalous behaviours to classifying anomalous behaviour types through clustering techniques.

Methodological recommendations, model steps: For the future research, it would be beneficial to incorporate the following information into the AIS data: the heading, navigational status and duration or time elapsed (to verify whether trips have the same duration). Information about distances from ship to objects or other ships would also be interesting. As a first improvement for the features it is recommended to add a time element. This time element can be defined by indicating whether a ship is operating in the morning, afternoon, evening, or at night. Additionally, the four seasons could be added as a feature as this relates to the traffic density on the waterways. Alternatively, traffic density or interaction with other ships could be incorporated into the model, but determining the local traffic density at a given moment in time is challenging. In Chapter 3 multiple features were proposed for ship abnormal behaviour types. It is recommended to include the detour factor, maximum drift angle, accumulative COG change and delta COG (Rong et al., 2024).

Validation recommendations: It is recommended to further scale the model, both in space and in time. From one tile in the North Sea to the entire North Sea covered with tiles, or even globally. Different embeddings for each tile can be analysed, taking into account various zoom levels of the tiles and the positioning of their boundaries. In addition, the model can be tested using publicly available American AIS data. This will allow for comparisons between behaviours observed in the Dutch part of the North Sea and those in American waters. Additionally, behaviours and features of maritime vessels can be compared with inland vessels. It is recommended to use the model for a longer duration than the current two days, around three to five years, to assess how the embeddings deviate with a longer time duration and to verify the effectiveness of the detection, including additional global detection. These checks can also be conducted using data containing all vessel type codes, without filtering for cargo and tanker ships. Furthermore, it is advisable to test a wider range or drifting ships and anomalous behaviour types. Additionally, the model has not yet been evaluated for performance, particularly regarding the accuracy of its detection. This should be validated using a confusion matrix, for example.

Operational recommendations

With the current model, a demonstration or interactive workshop can be given regarding its functionality by displaying the embedding and the outlier detection of abnormal behaviour with its trajectories. This was illustrated in Chapter 5 about the results, and with the workshop (see Appendix B). The detection of abnormal behaviour by operators using the model can be compared to the detection of abnormal behaviour by the operators' current methods in a test environment. Additionally, it is interesting to explore whether a similar method can contribute to the detection of security aspects in maritime traffic. To operationalize the model, the following steps are recommended. First, embeddings should be created for each tile in the North Sea. These embeddings should encompass trips that include AIS data from a period of at least three to five years, preferably as recent as possible. Before extending the duration, it would be beneficial to first test the comparison of embeddings from different seasons or from single years. When determining the minimum duration of the AIS data, it is important to consider changes in the spatial layout of the North Sea over time, societal events that may affect navigational behaviour and movements (such as during the COVID-19 restrictions and the blockage of the Suez Canal), and variations in weather conditions, including exceptional weather events.

During this research, the Microsoft Planetary Computer hub was utilized for larger calculations, however, this was taken out of service midway through the project. While Delft Blue was an alternative, the time required to learn the new program prevented its implementation in this research. Additionally, there was an aim to use labeled data, but the process of obtaining additional data proved to be time-consuming due to privacy laws and application procedures. In the field of monitoring maritime traffic with AIS data combined with machine learning techniques, there are still many opportunities to explore. Ensuring the safety and security of maritime traffic in the North sea is urgently needed due to the rapid increase in wind turbines, developments in maritime traffic and geopolitical tensions.

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A

Visit Coast Guard Center

On July 10 2024, a visit was made at the Coast Guard centre in Den Helder. This gave the opportunity to know more about the duties of the Coast Guard, to show the progress of the model for the research and to ask questions to the Coast Guard and to operators of the operational center regarding the research. The next four pages show the key points of the visit in Dutch ('Hoofdpunten bezoek kustwacht 10-07-2024') and translated to English ('Main points visit Coast Guard 10-07-2024').

Hoofdpunten bezoek kustwacht 10-07-2024

Jessica en Solange

Aanwezigen: Rein de Lange (beleidsadviseur kustwacht NL), Arnold Boomstra (Innovatie en inlichtingen kustwacht NL), Nienke Veldhuizen (Maritime Securty Officer kustwacht NL), Gert-Jan Post (NVWA), Solange van der Werff (TU Delft), Jessica van den Heuvel (TU Delft).

Algemeen over de Kustwacht

- De Kustwacht voert opdrachten uit voor de volgende ministers: de Minister van Infrastructuur en Waterstaat, de Minister van Justitie en Veiligheid, de Minister van Financiën, de Minister van Economische Zaken en Klimaat en de Minister van Landbouw, Natuur en Voedselkwaliteit. Daarbij werkt de Kustwacht samen met o.a. NVWA, Douane, Politie, Marechaussee, RWS.
- Investeringen worden volgens een verdeelsleutel over al deze partijen verdeeld.
- Er zijn veel verschillende afbakeningen van werkterreinen, bijv. SAR vs survey/monitoren vs luchtruim vs economische zone. Dit kan operaties bemoeilijken, omdat er soms andere landen verantwoordelijk zijn voor een bepaalde taak in een bepaald gebied.
- De komende tijd gaat de Kustwacht enorm uitbreiden qua personeel. Het is moeilijk om goede mensen te vinden vanwege de locatie in Den Helder, maar ook omdat vooralsnog geeist wordt dat mensen hebben gevaren (en die vijver is klein). Met betere technische ondersteuning zou het waarschijnlijk makkelijker worden voor mensen met een andere (nautische) achtergrond om het werk te doen.

Beeldopbouw

- De term "beeldopbouw" wordt veel gebruikt: het kan beschreven worden als het samenbrengen van verschillende bronnen van informatie om in te schatten wat er ergens gebeurt.
- Het is voor operators soms moeilijk om rekening te houden met actuele regels, zoals invaarverboden in natuurgebieden of bij militaire oefeningen, of wie er geautoriseerd is om een windmolenpark in te varen (permits variëren van een paar uur tot een paar dagen). Een applicatie waarbij verschillende kaartlagen aan elkaar gekoppeld worden zou wenselijk zijn, om actueel te zien of een bepaald schip geautoriseerd is om zich er te begeven.
- De Kustwacht vervult de monitoring/handhavingstaak op basis van informatie uit twee hoofdrichtingen:
    - Het monitoren van de actuele situatie door middel van schermen en communicatiemiddelen (d.m.v. meldingen). Op de schermen zijn actuele scheepsposities te zien, en indien nodig kan een bepaalde historie (traject, herkomst) worden opgevraagd. Hierbij wordt ook veel gebruik gemaakt van openbare bronnen zoals MarineTraffic. De operators houden dus zelf op basis van actuele posities in de gaten of schepen zich bijvoorbeeld ongewoon lang ergens ophouden, of precies boven een pijpleiding stil gaan liggen.
    - "Intel": onder andere door zaken die aan het licht komen binnen de MIK-NL (Maritiem Informatie Knooppunt), hierbij zitten diverse autoriteiten (politie, douane, kustwacht, etc) fysiek samen om informatie uit te wisselen.
- Als hier opmerkelijke dingen in naar voren komen, kan er bijvoorbeeld contact gezocht worden met de schipper of gevraagd worden of het vliegtuig poolshoogte gaat nemen.

Handelen

- Op dit moment worden er ook alarmen afgegeven, maar dit zijn er eigenlijk al te veel, waardoor het risico bestaat dat ze niet meer serieus worden genomen. De operator gaf aan dat als er bijv elke 10 minuten een alarm afgaat, dit teveel afleidt en ervoor zou kunnen zorgen dat ze niet worden opgevolgd.
- De operator gaf ook aan dat als er een alarm is, hij eigenlijk meteen wil kunnen zien wat de reden ervoor is (wat maakt dat het schip als afwijkend wordt aangemerkt).
- De context speelt naast ervaring een belangrijke rol bij het inschatten en bepalen of vaargedrag afwijkend is of te verklaren valt (voorbeeld permits).
- Hoe snel afwijkend gedrag opgemerkt kan worden verschilt per situatie.
- Er wordt direct veel geïnterpreteerd en meteen naar verschillende bronnen gekeken. Op basis daarvan wordt vaak het één en ander even aangekeken. Bijvoorbeeld:
  - Tankers die ergens gaan stil liggen om een hogere olieprijs af te wachten.
  - Schepen die plotseling vertragen, omdat ze weten dat hun terminal pas later beschikbaar is. De operator zou dan even kijken in de “ETA” van het schip om te zien hoe laat het ergens aan zou moeten komen.
- In sommige gevallen is juist meteen duidelijk dat er actie nodig is:
  - Bij de Julietta D. was meteen duidelijk dat er iets mis was, vanwege de kleine afstand tussen twee schepen in het ankergebied. Daarbij was de orientatie van het schip anders dan verwacht.
  - Schepen die pal boven een elektriciteitskabel of pijpleiding liggen, zijn ook meteen ‘verdacht’.

Afwijkingen herkennen

- De EMSA categorisering was bij de meesten in de ruimte wel bekend. Het “regelgebaseerd” opereren werd ook wel herkend. Het leek ook goed over te komen welke ‘ruimte’ we nog proberen te vullen met onze aanpak.
- Er wordt snel een link gelegd naar de praktijk en hoe de aanpak daar zou (kunnen) werken. Ze zouden graag zien dat dit in een soort workshop vorm wordt gedaan. We hebben aangegeven dat dit op termijn zou kunnen, maar buiten de scope van Jessica’s onderzoek ligt.
- Er werd aangegeven dat de implementatie van dit soort nieuwe technieken in kleine stapjes moet gaan, zodat de veranderingen voor operators niet te groot worden.

Conclusies/verdere ideeën

- Omdat het moeilijk is om meteen de goede balans te vinden in het aantal anomalies dat een alarm veroorzaakt, kan ik me voorstellen dat je eerst een applicatie maakt waarin een operator kan zien welke schepen zich het meest afwijkend gedragen, zonder daar een alarm aan te koppelen, dat ze tussen hun werkzaamheden door af en toe kunnen raadplegen. Hiermee zouden ze misschien kunnen ‘wennen’ aan de AI-ondersteuning en er vertrouwen in krijgen.
- Sommige gedragingen zijn mogelijk niet eens bekend, hier kan deze aanpak aan bijdragen.

Main points visit Coast Guard 10-07-2024

Jessica en Solange

Attendees: Rein de Lange (beleidsadviseur kustwacht NL), Arnold Boomstra (Innovatie en inlichtingen kustwacht NL), Nienke Veldhuizen (Maritime Securty Officer kustwacht NL), Gert-Jan Post (NVWA), Solange van der Werff (TU Delft), Jessica van den Heuvel (TU Delft).

General about the Coast Guard

- The Coast Guard carries out tasks for the following ministers: the Minister of Infrastructure and Water Management, the Minister of Justice and Security, the Minister of Finance, the Minister of Economic Affairs and Climate and the Minister of Agriculture, Nature and Food Quality. In doing so, the Coast Guard cooperates with NVWA, Customs, Police, Marechaussee, RWS, among others.
- Investments are shared among all these parties according to a distribution key.
- There are many different demarcations of working areas, e.g. SAR vs survey/monitoring vs airspace vs economic zone. This can complicate operations, because sometimes other countries are responsible for a particular task in a particular area.
- In the coming period, the Coast Guard is going to expand enormously in terms of personnel. It is difficult to find good people, because of the location in Den Helder, but also because, for the time being, it is required that people have sailed. With better technical support, it would probably become easier for people with a different (nautical) background to do the job.

Image building

- The term 'image building' is widely used: it can be described as bringing together different sources of information to assess what is happening somewhere.
- It is sometimes difficult for operators to take into account current rules, such as entry bans in nature reserves or military exercises, or who is authorised to enter a wind farm (permits vary from a few hours to a few days). An application linking different map layers would be desirable, to see up-to-date whether a particular vessel is authorised to enter.
- The Coast Guard performs the monitoring/enforcement task based on information from two main directions:
    - Monitoring the current situation through screens and means of communication (through reports). The screens show current vessel positions, and if necessary, a certain history (trajectory, origin) can be requested. This also makes extensive use of public sources such as MarineTraffic. The operators thus monitor themselves, based on current positions, whether, for example, ships are holding up somewhere unusually long, or stopping precisely over a pipeline.
    - "Intel": among other things, due to cases that come to light within the MIK-NL (Maritiem Informatie Knooppunt), where various authorities (police, customs, coastguard, etc) physically sit together to exchange information.
- If noteworthy things come to light in this, the skipper can be contacted, for example, or asked if the aircraft will go and take a look.

Act

- At the moment, alarms are also issued, but there are actually too many of them already, risking that they are no longer taken seriously. The operator indicated that if e.g. an alarm goes off every 10 minutes, this is too distracting and could cause them not to be followed up.
- The operator also indicated that if there is an alarm, he actually wants to be able to see immediately what the reason for it is (what makes the ship marked as anomalous).
- In addition to experience, context plays an important role in assessing and determining whether sailing behaviour is deviant or explainable (example permits).
- How quickly anomalous behaviour can be noticed varies from situation to situation.
- A lot is immediately interpreted and various sources are immediately looked at. Based on that, things are often looked at for a while. For example:
    - Tankers that come to a halt somewhere to await a higher oil price.
    - Ships that suddenly slow down, because they know their terminal won't be available until later. The operator would then take a quick look at the ship's ‘ETA’ to see what time it should arrive somewhere.
- In some cases, on the contrary, it is immediately clear that action is needed:
    - In the case of the Julietta D., it was immediately clear that something was wrong, because of the small distance between two ships in the anchorage area. In addition, the ship's orientation was different than expected.
    - Ships lying directly over a power cable or pipeline are also immediately ‘suspicious’.

Recognize anomalies

- The EMSA categorisation was familiar to most in the room. The “rule-based” operation was also well recognised. It also seemed to come across well what ‘space’ we are still trying to fill with our approach.
- A link is quickly made to practice and how the approach could (potentially) work there. They would like to see this done in some kind of workshop format. We indicated that this could eventually be done, but is beyond the scope of Jessica's research.
- It was indicated that the implementation of these kinds of new techniques should be done in small steps, so that the changes for operators do not become too big.

Conclusions/further ideas

- Since it is difficult to immediately get the right balance in the number of anomalies that trigger an alarm, I can imagine first creating an application where an operator can see which ships are behaving the most anomalous, without attaching an alarm to it, that they can consult from time to time in between their work. This might allow them to ‘get used to’ AI support and gain confidence in it.
- Some behaviours may not even be known, this is where this approach could help.

B
Opinion specialists (workshop)

On the third of June 2024 a workshop (in Dutch and partly in English) was conducted at a gathering regarding Nautical Safety and AIS data. At this gathering specialists were present from the Coast guard, Rijkswaterstaat, MARIN, Deltares and TU Delft. During the workshop the version of the model at that time until the embedding (DensMap) was shown, which followed from AIS data from 31-01-2021 and 01-02-2021 at the time of the incident of the Julietta D including all types of vessels and part of the inland waters. With visualisations, the sailed trip could be shown from one or multiple points in the embedding, this allowed trips of ships with the same features or behaviour to be shown (see Figures B.1 and B.2). In addition, features of the groups were displayed. During the workshop specialists provided comments and suggestions, which are listed in the table below (see Table B.1).

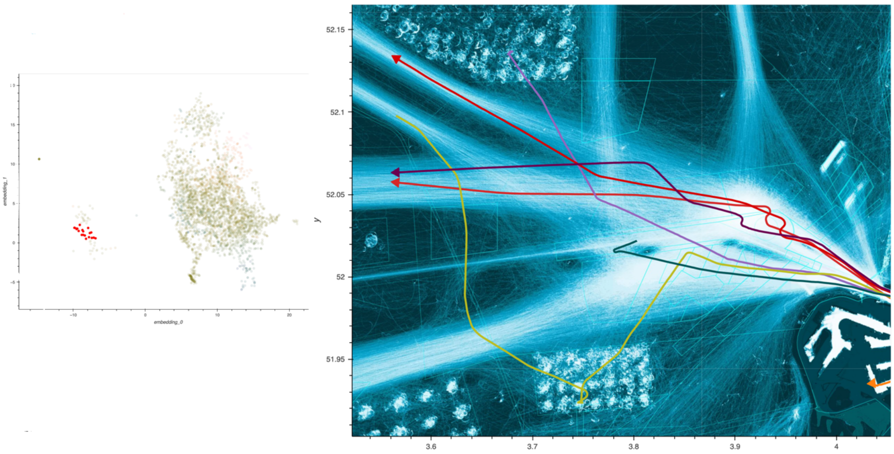

Figure B.1: Example figures of workshop of sailing ships with detours

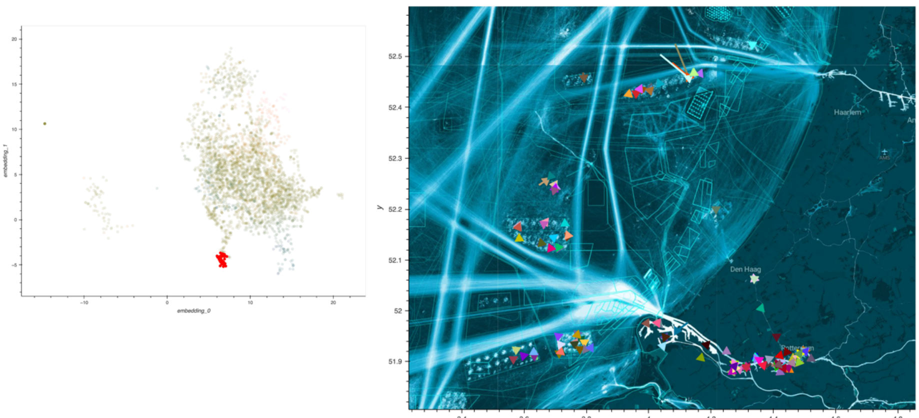

Figure B.2: Example figures of workshop of anchored ships

Table B.1: Comments or suggestions specialists

Kenmerk (feature)	Type gedrag (type of behavior)	Anders (other)
Vlaggenstaat, is te herleiden uit mmsi nummer.	Opzettelijk afwijkend gedrag	Afwijkend vaargedrag is niet per se onveilig
Verkeersregels	Vissersboten die kortstondig achter een groot schip aanvaren en vervolgens vissersgedrag lieten zien. Dit betrekking tot beveiliging (security)	Verander de inbedding (embedding) over tijd en kijk hoe de inbedding weergegeven wordt voor verschillende tijdstappen
Scheepsvaarwegen		Dat het model groepen kan maken zonder dat er van tevoren vesseltypes zijn meegegeven, geeft vertrouwen in het model.
Doel van het schip (ankeren of varen)		Wat zeggen de assen van de inbedding als je naar links/rechts/boven of onderen gaat?
Schip-schip interactie		Wat zeggen de puntjes in de inbedding? (De trajecten waren wel begrijpelijk)
Dichtheidskaart van vissers		Er is een lijst met onmanoeuvreerbaar schepen/NUC'ers (Not Under Command)
Diepgang van schepen		In de netwerkanalyse van worden onmanoeuvreerbare schepen ook genoemd
Route en niet-route gebonden schepen		Er is gelabelde data van drifters is te gebruiken als testcase.
		Er is een data rapport met meldingen lijst?

C

EMCIP taxonomy

The European Marine Casualty Information Platform (EMCIP) stores and analyses data on marine casualties and incidents in Europe. A codification was made for systematic investigation of marine casualties and incidents. Different elements from the root of events are connected to the consequences (see Figure C.1).

The EMCIP taxonomy (European Maritime Safety Agency, 2023):

- **Capsizing/Listing**: is a casualty where the ship no longer floats in the right-side-up mode due to negative initial stability (negative metacentric height), or transversal shift of the centre of gravity, or the impact of external forces.
  - **Capsizing**: when the ship is tipped over until disabled;
  - **Listing**: when the ship has a permanent heel or angle of loll.
- **Collision**: a casualty caused by ships striking or being struck by another ship, regardless of whether the ships are underway, anchored or moored. This type of casualty event does not include ships striking underwater wrecks. The collision can be with other ship or with multiple ships or ship not underway.
- **Contact**: a casualty caused by ships striking or being struck by an external object. The objects can be: Floating object (cargo, ice, other or unknown); Fixed object, but not the sea bottom; or Flying object.
- **Damage to equipment**: damage to equipment, system or the ship not covered by any of the other casualty type.
- **Grounding/stranding**: a moving navigating ship, either under command, under Power, or not under command, Drift(ing), striking the sea bottom, shore or underwater wrecks.
- **Fire/explosion**: an uncontrolled ignition of flammable chemicals and other materials on board of a ship:
  - **Fire**: is the uncontrolled process of combustion characterised by heat or smoke or flame or any combination of these.
  - **Explosion**: is an uncontrolled release of energy which causes a pressure discontinuity or blast wave.
- **Flooding/foundering**: is a casualty event when the ship is taking water on board.
  - **Foundering**: will be considered when the vessel has sunk. Foundering should only be regarded as the first casualty event if we do not know the details of the flooding which caused the vessel to founder. In the chain of events foundering can be the last casualty event in this case there is the need to add accidental events.
  - **Flooding**: refers to a casualty when a vessel takes water on board and can be:

    * **Progressive**: if the water flow is gradual.
    * **Massive**: if the water flow is extensive.

- **Hull failure**: a failure affecting the general structural strength of the ship.
- **Loss of control**: a total or temporary loss of the ability to operate or manoeuvre the ship, failure of electric power, or to contain on board cargo or other substances:
  - **Loss of electrical power**: is the loss of the electrical supply to the ship or facility;
  - **Loss of propulsion power**: is the loss of propulsion because of machinery failure;
  - **Loss of directional control**: is the loss of the ability to steer the ship;
  - **Loss of containment**: is an accidental spill or damage or loss of cargo or other substances carried on board a ship.
- **Missing**: a casualty to a ship whose fate is undetermined with no information having been received on the loss and whereabouts after a reasonable period of time.
- **Non-accidental events**: are intentional events as a result of illegal or hostile acts therefore they are not marine casualties or incidents. They are:
  - **Acts of war**: any act, against a ship or the people on board, by a State that would effectively terminate the normal international law of peacetime and activate the international law of war;
  - **Criminal acts**: any crime, including an act, omission, or possession under the laws of a State or local government, which poses a substantial threat to people on board of a ship or to property (e.g. terrorism, sabotage, piracy);
  - **Illegal discharge**: is an intentional discharge of polluting substances, oil or other noxious substances, from ships; and
  - **Other**: other intentional act that incur loss of or damage to a ship or environmental damage or harm to people on board.

Non-accidental events are not considered as marine casualties or incidents and are not covered by the scope of the Accident Investigation Directive (2009/18/EC).

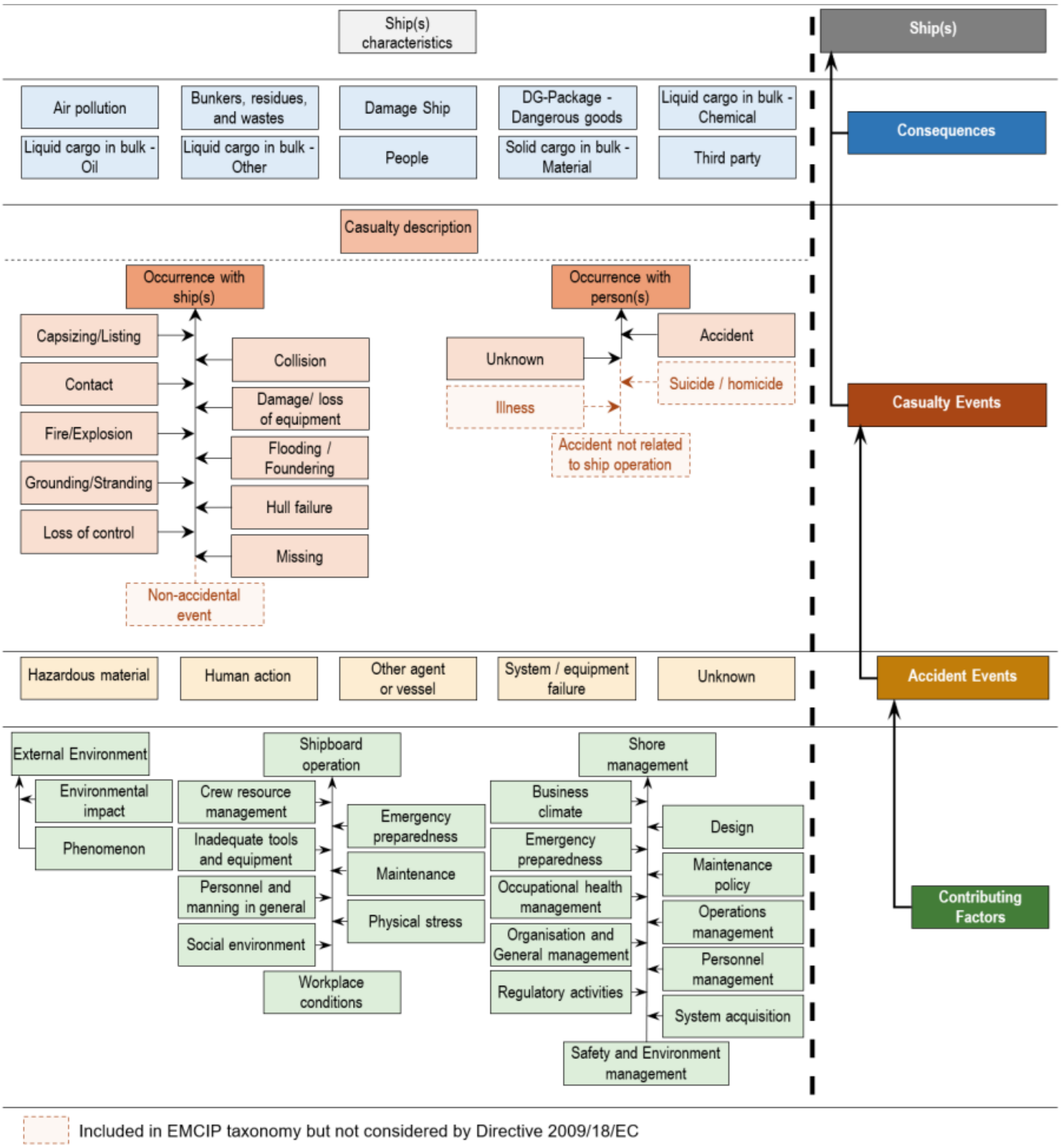

Figure C.1: EMCIP model with occurrence casualty event with a ship

Source: European Maritime Safety Agency (2023)

D

Vesseltype codes AIS data

Vesseltype codes in AIS data give a description of the ship and cargo classification. Marine Cadastre made an overview of all the vesseltype and group codes (NOAA Office for Coastal Management, 2024) (see next page). Cargo ships cover the AIS Vessel Code numbers 70 until 79 and for Vessel types 1003, 1004 and 1016 are included as well. Tankers cover the AIS Vessel Code numbers 80 until 89 and for Vessel Types 1017 and 1024 are included as well.

Vessel Group (2018) key

	Cargo
	Fishing
	Military
	Not Available
	Other
	Passenger
	Pleasure Craft/Sailing
	Tanker
	Tug Tow

AIS Vessel Type and Group Codes used by the Marine Cadastre Project
2018 -05-23

sources: U.S. Coast Guard, NOAA, BOEM

	Vessel Group (2018)	Vessel Type (2018)	AIS Vessel Code	AIS Ship & Cargo Classification
	Not Available	0	0	Not available or no ship, default
	Other	1-19	1-19	Reserved for future use
	Other	20	20	Wing in ground (WIG), all ships of this type
	Tug Tow	21	21	Wing in ground (WIG), hazardous category A
	Tug Tow	22	22	Wing in ground (WIG), hazardous category B
	Other	23	23	Wing in ground (WIG), hazardous category C
	Other	24	24	Wing in ground (WIG), hazardous category D
	Other	25	25	Wing in ground (WIG), reserved for future use
	Other	26	26	Wing in ground (WIG), reserved for future use
	Other	27	27	Wing in ground (WIG), reserved for future use
	Other	28	28	Wing in ground (WIG), reserved for future use
	Other	29	29	Wing in ground (WIG), reserved for future use
	Fishing	30	30	Fishing
	Tug Tow	31	31	Towing
	Tug Tow	32	32	Towing: length exceeds 200m or breadth exceeds 25m
	Other	33	33	Dredging or underwater operations
	Other	34	34	Diving operations
	Military	35	35	Military operations
	Pleasure Craft/Sailing	36	36	Sailing
	Pleasure Craft/Sailing	37	37	Pleasure Craft
	Other	38	38	Reserved
	Other	39	39	Reserved
	Other	40	40	High speed craft (HSC), all ships of this type
	Other	41	41	High speed craft (HSC), hazardous category A
	Other	42	42	High speed craft (HSC), hazardous category B
	Other	43	43	High speed craft (HSC), hazardous category C
	Other	44	44	High speed craft (HSC), hazardous category D
	Other	45	45	High speed craft (HSC), reserved for future use
	Other	46	46	High speed craft (HSC), reserved for future use
	Other	47	47	High speed craft (HSC), reserved for future use
	Other	48	48	High speed craft (HSC), reserved for future use
	Other	49	49	High speed craft (HSC), no additional information
	Other	50	50	Pilot Vessel
	Other	51	51	Search and Rescue vessel
	Tug Tow	52	52	Tug
	Other	53	53	Port Tender
	Other	54	54	Anti-pollution equipment
	Other	55	55	Law Enforcement
	Other	56	56	Spare - for assignment to local vessel
	Other	57	57	Spare - for assignment to local vessel
	Other	58	58	Medical Transport
	Other	59	59	Ship according to RR Resolution No. 18

	Passenger	60	60	Passenger, all ships of this type
	Passenger	61	61	Passenger, hazardous category A
	Passenger	62	62	Passenger, hazardous category B
	Passenger	63	63	Passenger, hazardous category C
	Passenger	64	64	Passenger, hazardous category D
	Passenger	65	65	Passenger, reserved for future use
	Passenger	66	66	Passenger, reserved for future use
	Passenger	67	67	Passenger, reserved for future use
	Passenger	68	68	Passenger, reserved for future use
	Passenger	69	69	Passenger, no additional information
	Cargo	70	70	Cargo, all ships of this type
	Cargo	71	71	Cargo, hazardous category A
	Cargo	72	72	Cargo, hazardous category B
	Cargo	73	73	Cargo, hazardous category C
	Cargo	74	74	Cargo, hazardous category D
	Cargo	75	75	Cargo, reserved for future use
	Cargo	76	76	Cargo, reserved for future use
	Cargo	77	77	Cargo, reserved for future use
	Cargo	78	78	Cargo, reserved for future use
	Cargo	79	79	Cargo, no additional information
	Tanker	80	80	Tanker, all ships of this type
	Tanker	81	81	Tanker, hazardous category A
	Tanker	82	82	Tanker, hazardous category B
	Tanker	83	83	Tanker, hazardous category C
	Tanker	84	84	Tanker, hazardous category D
	Tanker	85	85	Tanker, reserved for future use
	Tanker	86	86	Tanker, reserved for future use
	Tanker	87	87	Tanker, reserved for future use
	Tanker	88	88	Tanker, reserved for future use
	Tanker	89	89	Tanker, no additional information
	Other	90	90	Other Type, all ships of this type
	Other	91	91	Other Type, hazardous category A
	Other	92	92	Other Type, hazardous category B
	Other	93	93	Other Type, hazardous category C
	Other	94	94	Other Type, hazardous category D
	Other	95	95	Other Type, reserved for future use
	Other	96	96	Other Type, reserved for future use
	Other	97	97	Other Type, reserved for future use
	Other	98	98	Other Type, reserved for future use
	Other	99	99	Other Type, no additional information
	Other	100 to 199	100 to 199	Reserved for regional use
	Other	200 to 255	200 to 255	Reserved for future use
	Other	256 to 999	256 to 999	No designation

	Vessel Group (2018)	VesselType (2018)		AVIS Vessel Service
	Other	-	-	null
	Fishing	1001	-	Commercial Fishing Vessel
	Fishing	1002	-	Fish Processing Vessel
	Cargo	1003	-	Freight Barge
	Cargo	1004	-	Freight Ship
	Other	1005	-	Industrial Vessel
	Other	1006	-	Miscellaneous Vessel
	Other	1007	-	Mobile Offshore Drilling Unit
	Other	1008	-	Non-vessel

	Other	1009	-	NON-VESSEL
	Other	1010	-	Offshore Supply Vessel
	Other	1011	-	Oil Recovery
	Passenger	1012	-	Passenger (Inspected)
	Passenger	1013	-	Passenger (Uninspected)
	Passenger	1014	-	Passenger Barge (Inspected)
	Passenger	1015	-	Passenger Barge (Uninspected)
	Cargo	1016	-	Public Freight
	Tanker	1017	-	Public Tankship/Barge
	Other	1018	-	Public Vessel, Unclassified
	Pleasure Craft/Sailing	1019	-	Recreational
	Other	1020	-	Research Vessel
	Military	1021	-	SAR Aircraft
	Other	1022	-	School Ship
	Tug Tow	1023	-	Tank Barge
	Tanker	1024	-	Tank Ship
	Tug Tow	1025	-	Towing Vessel

E

Feature options and spatial properties

Table E.1: AIS data specifications

Source: Spire Global (2024)

AIS data columns		
Data columns	**Description**	**range and unit**
timestamp [string]	ISO8601 formatted timestamp in UTC of the time the AIS message was transmitted	UTC
latitude [float]	Vessel latitude in degrees (North = positive, South = negative)	-90 to +90
longitude [float]	Vessel longitude in degrees (East = positive, West = negative)	-180 to +180
sog	Speed Over Ground	0 till 102.2 knots (102.3: not available)
cog	Course Over Ground	0 till 359.9 degrees (360.0: not available)
rot	Vessel rate of turn	-127 till 127 degrees (-128: not available)
length	Vessel length from ship dimensions to_bow and to_stern	meters
width	Vessel width from ship dimensions to_port and to_starboard	meters
heading	Vessel true heading	0 till 359 degrees (511: not available)
maneuver	Vessel maneuver code	0 (not available; default), 1 (not engaged in special maneuver), 2 (engaged in special maneuver)

Table E.2: AIS data, additional columns added with functions of MovingPandas (f) or manually added (m)

Source: (MovingPandas develeopers, 2024)

Additional columns AIS data		
Data columns	**Description**	**range and or unit**
acceleration (f)	Acceleration between current point and the previous	For geographic projections [m/s2] for other projections [CRS units/s2]
angular difference (f)	Calculated as absolute smaller angle between direction for points along the trajectory. Not reliable, because absolute diff!	[0,180.0]
direction (f)	Direction between consecutive locations	[0,360] in degrees, starting from North turning clockwise
distance (f)	Computed between the current point and the previous	If no units have been declared for geographic projections (EPSG:4326 WGS84), in meters for other projections, in CRS units
speed (f)	Computed between the current point and the previous	If no units have been declared for geographic projections [m/s], for other projections [CRS units/sec]
time elapsed (m)	Time elapsed between 2 signals	seconds
speed difference (m)	Diff. in speed between current point and the previous	see speed
cog difference (m)	Diff. in cog between current point and the previous	see cog
direction difference (m)	Diff. in direction between current point and the previous	see direction
ROT	Newly defined ROT instead of original rot. Equal to angular difference / time elapsed in minutes	degrees/ minutes

Table E.3: Feature options tsfresh

Source: (Maximilian Christ et al., 2024)

Features tsfresh		
abs_energy	absolute_maximum	absolute_sum_of_changes
agg_autocorrelation	agg_linear_trend	approximate_entropy
ar_coefficient	augmented_dickey_fuller	autocorrelation
benford_correlation	binned_entropy	c3
change_quantiles	cid_ce	count_above
count_above_mean	count_below	count_below_mean
cwt_coefficients	energy_ratio_by_chunks	fft_aggregated
fft_coefficient	first_location_of_maximum	first_location_of_minimum
fourier_entropy	friedrich_coefficients	has_duplicate
has_duplicate_max	has_duplicate_min	index_mass_quantile
kurtosis	large_standard_deviation	last_location_of_maximum
last_location_of_minimum	lempel_ziv_complexity	length
linear_trend	linear_trend_timewise	longest_strike_above_mean
longest_strike_below_mean	matrix_profile	max_langevin_fixed_point
maximum	mean	mean_abs_change
mean_change	mean_n_absolute_max	mean_second_derivative_central
median	minimum	number_crossing_m
number_cwt_peaks	number_peaks	partial_autocorrelation
percentage_of_reoccurring_datapoint_to _all_datapoints	percentage_of_reoccurring_values_to _all_values	permutation_entropy
quantile	query_similarity_count	range_count
ratio_beyond_r_sigma	ratio_value_number_to_time_series_length	root_mean_square
sample_entropy	set_property	skewness
spkt_welch_density	standard_deviation	sum_of_reoccurring_data_points
sum_of_reoccurring_values	sum_values	symmetry_looking
time_reversal_asymmetry_statistic	value_count	variance
variance_larger_than_standard_deviation	variation_coefficient	

Table E.4: Applied spatial properties for drifters and dragging anchors

Source: (Free Software Foundation, 1991)

Category	Spatial property	Dutch description in QGIS
Navigation	Traffic Separation Scheme (TSS)	Verkeersscheidingsstelsel
	Approach area	Aanloopgebied (hetzelfde als huidige_aanloopgebieden)
	Anchorage area	Ankergebieden
North Sea	Economic zone North Sea	dhv_exl_economische_zone
Wind	Permitted wind farms safety zones	Vergunde windparken veiligheid-zones

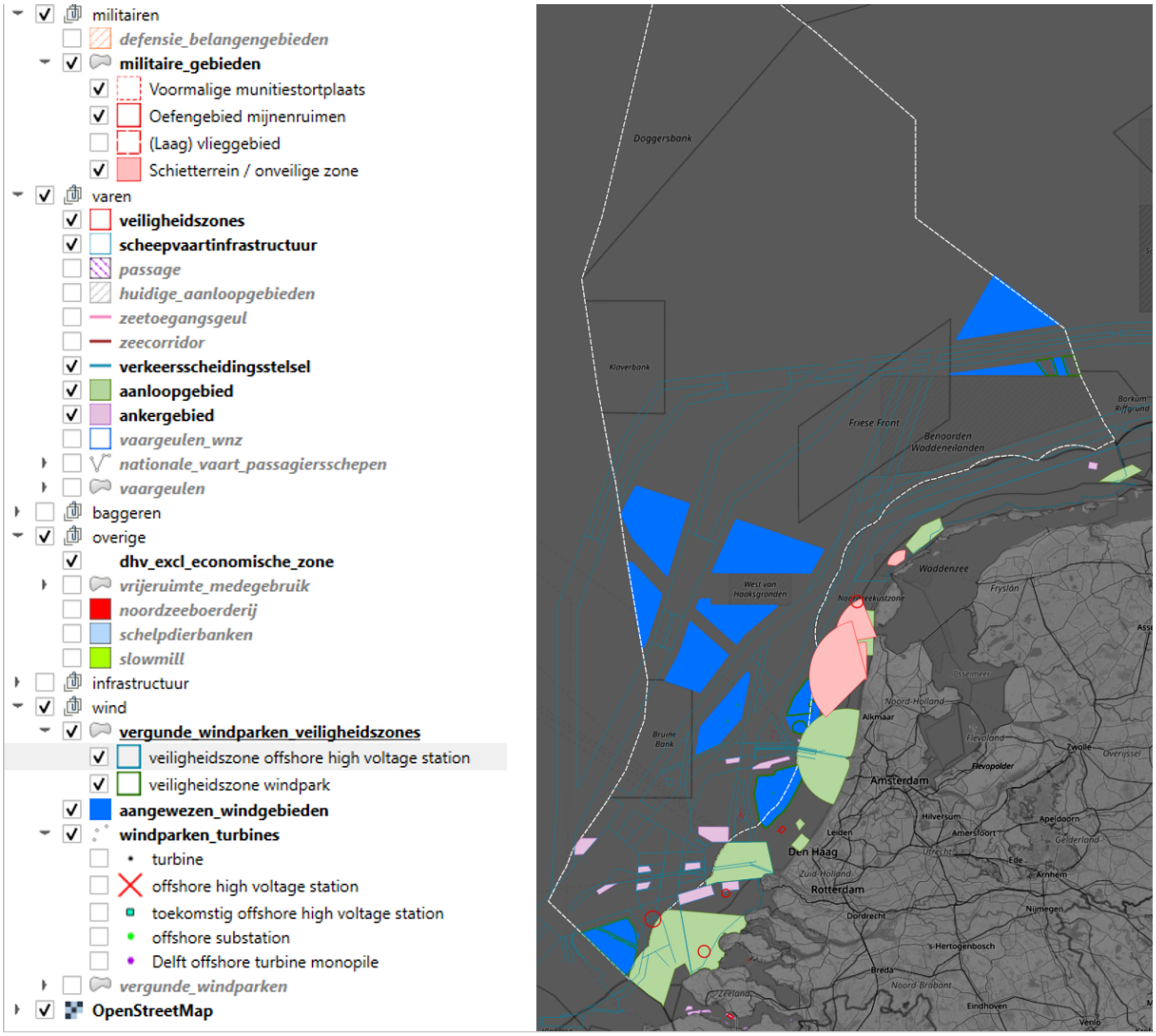

Figure E.1: Selection of optional spatial properties

Source: (Free Software Foundation, 1991)

Table E.5: Optional spatial properties

Source: (Free Software Foundation, 1991)

Category	Spatial property	Dutch description in QGIS
Military	Military areas (former ammunition dump, mine clearance training area, firing range/unsafe zone)	Militaire gebieden (voormalige munitiestrotplaats, oefengebied mijnenruimen, schietterrein/ onveilige zone)
Navigation	Traffic separation scheme	Verkeersscheidingsstelsel
	Shipping infrastructure	Scheepsinfrastructuur
	Approach area	Aanloopgebied (hetzelfde als huidige_aanloopgebieden)
	Anchorage area	Ankergebieden
	Safety zones	Veiligheidszones
	Passage through windfarm	Passage
Dredging	-	-
North Sea	Economic zone North Sea	dhv_exl_economische_zone
Infrastructure	Monitoring network (buoy, platform, platform+buoy, measuring pole)	Meetnet (boei, platform, platform+boei, meetpaal)
	Control cables north sea, electricity cables, pipelines, telecom cables	Bedieningskabels_noordzee, electra_kabels_noordzeek pijleidingen_noordzee, telecom_kabels_noordzee
Wind	Permitted wind farms safety zones (offshore high voltage station and windpark)	Vergunde windparken veiligheidzones (offshore high voltage station and windpark)
	Designated wind areas	Aangewezen windgebieden
	Wind farms_turbines (turbine, offshore high-voltage substation, future offshore high-voltage substation, offshore substation, Delft offshore turbine monopile)	windparken_turbines (turbine, offshore hoogspanningsstation, toekomstig offshore hoogspanningsstation, offshore substation, Delft offshore turbine monopile)
	Permitted wind farms (in use, under construction, in design, undern development)	Vergunde windparken (in gebruik, in aanbouw, in ontwerp, in ontwikkeling)

F
Details wind farms North Sea

The wind farms are under construction. The AIS data covers the first 2 months of 2022, so it will be established which wind farms were under construction in this period (Rijksoverheid, 2024):

1. Borssele: In use since 2021.
2. Hollandse Kust Zuid: Under construction since 2021.
3. Hollandse Kust Noord: Under construction since October 2022.
4. Hollandse Kust West: The construction started in 2023.
5. IJmuiden Ver - Tender 2024
6. Nederwiek - Tender 2026
7. Ten noorden van Waddeneilanden - Tender 2027 (The Gemini WindFarm is in use since 2017)
8. Doordewin - Tender 2027

The wind farms that should be taken into account for January and February 2022 are the numbers 1 and 2 of which 2 is present in the area of the AIS data (visible in appendix E).

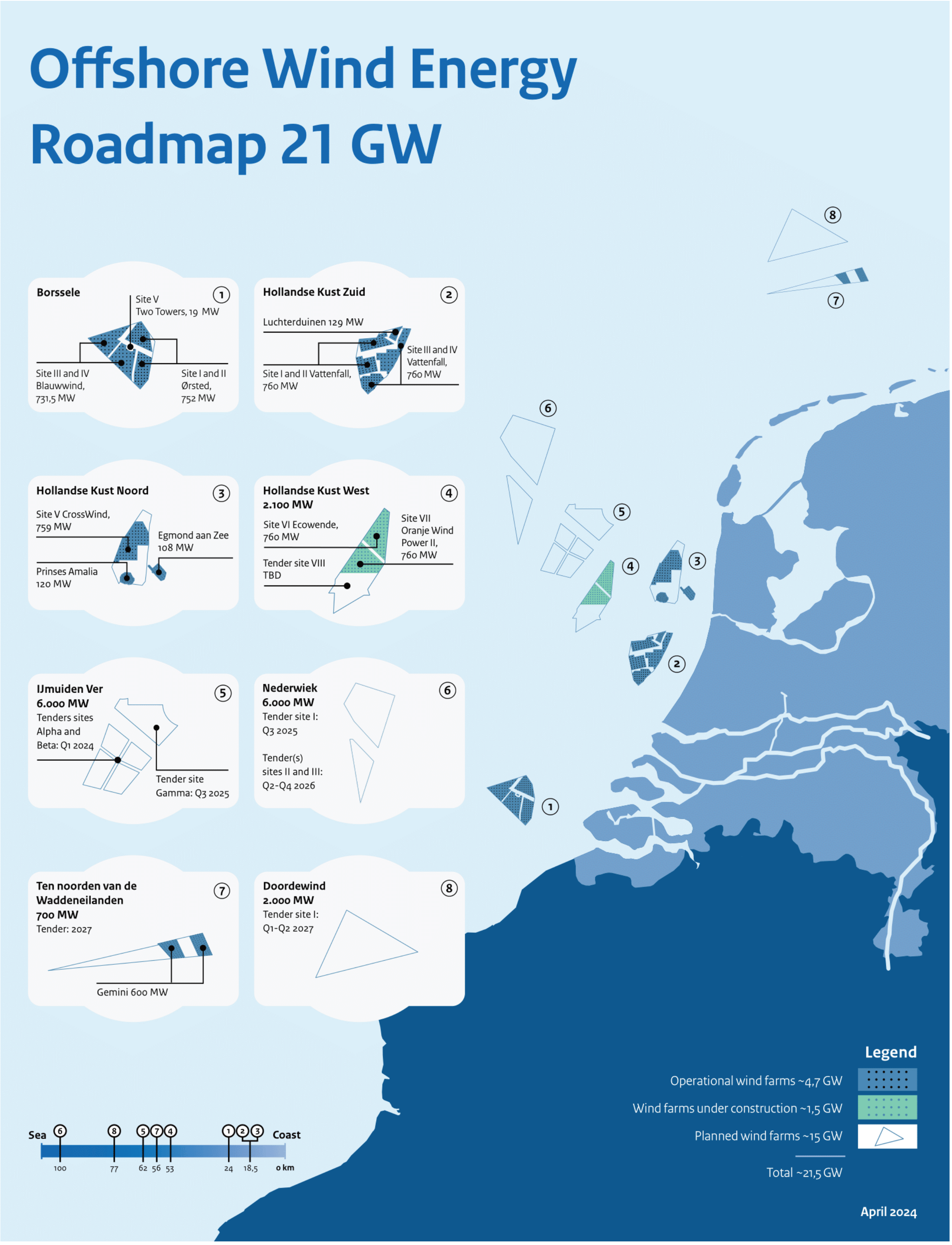

Figure F.1: Offshore Wind Energy Roadmap April 2024

Source: (Netherlands Enterprise Agency, 2024)

G

Distribution of features from AIS data

To visualize the distribution of the features, a histogram has been created using features from 1-hour trips.

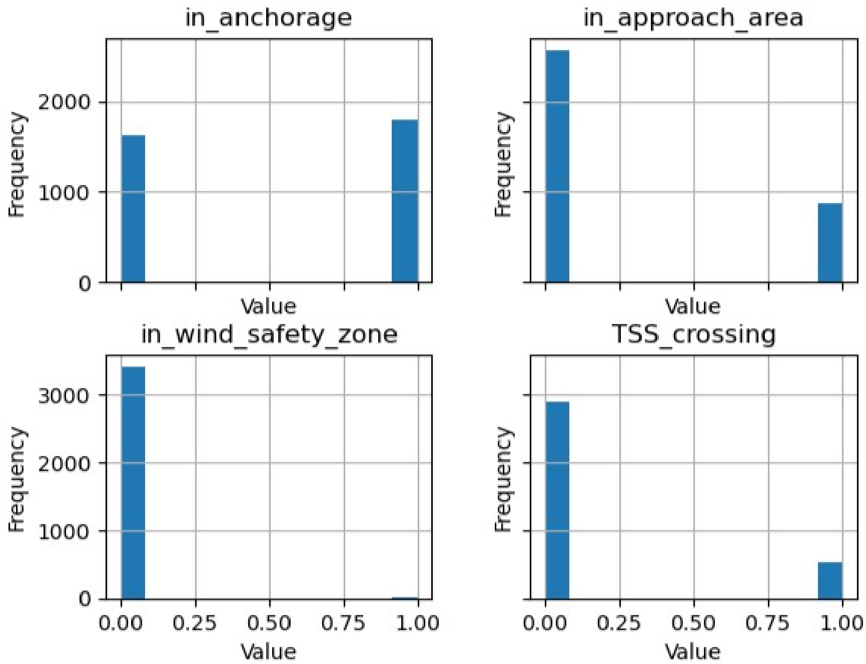

Figure G.1: Histrogram of spatial properties, with trips of 1 hour

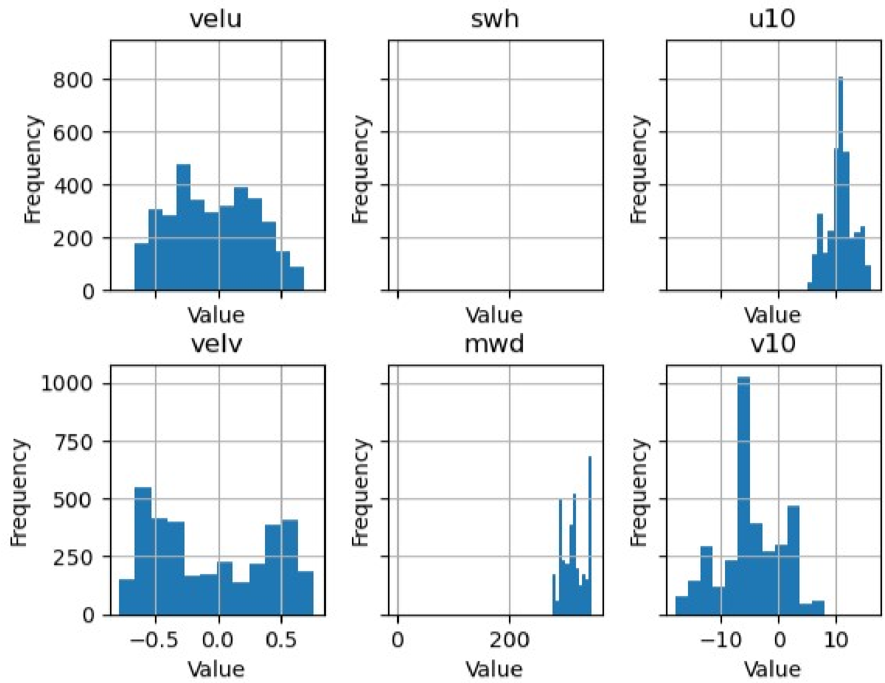

Figure G.2: Histrogram of metocean conditions: SOG, with trips of 1 hour

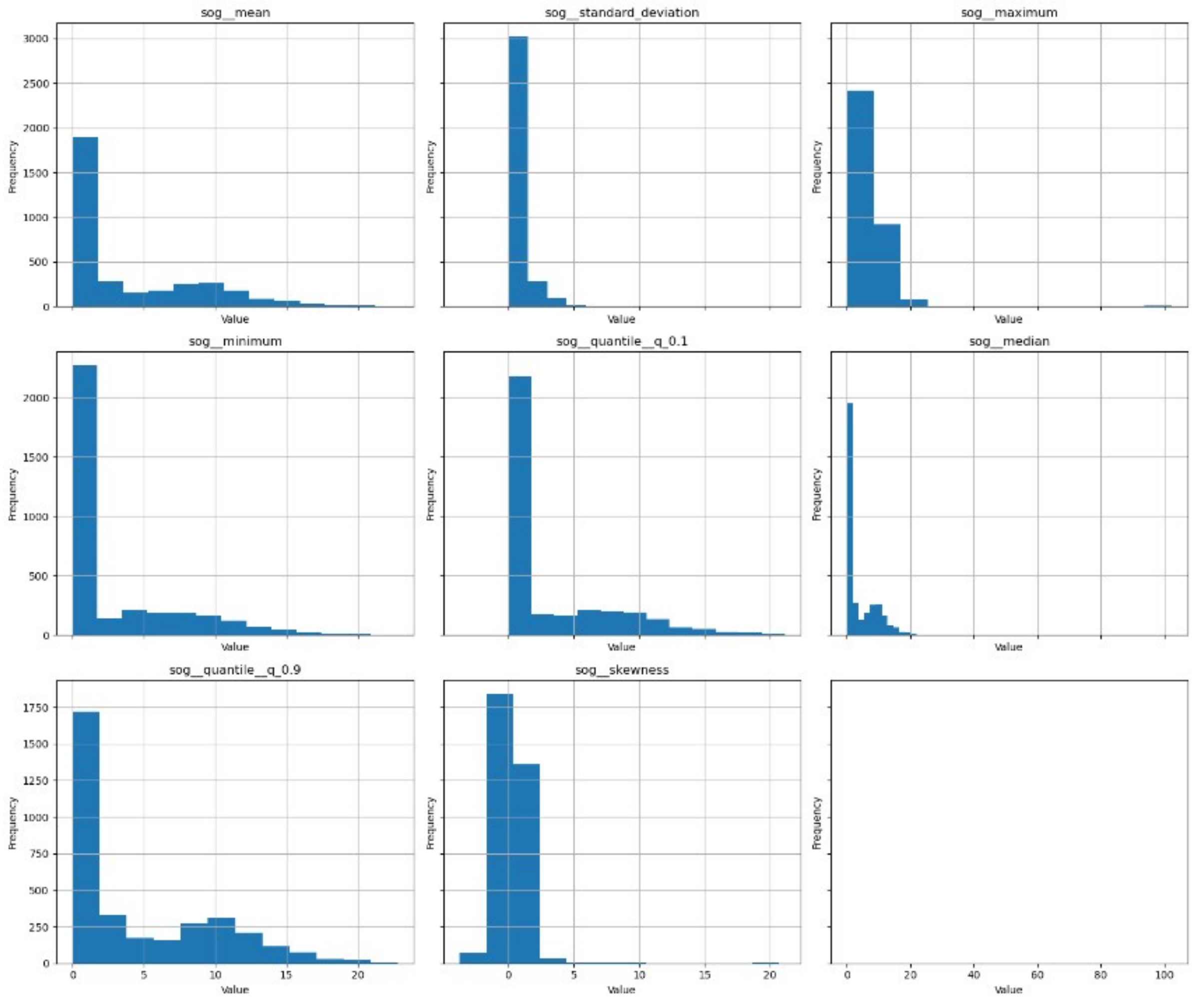

Figure G.3: Histrogram of ship motion features: SOG, with trips of 1 hour

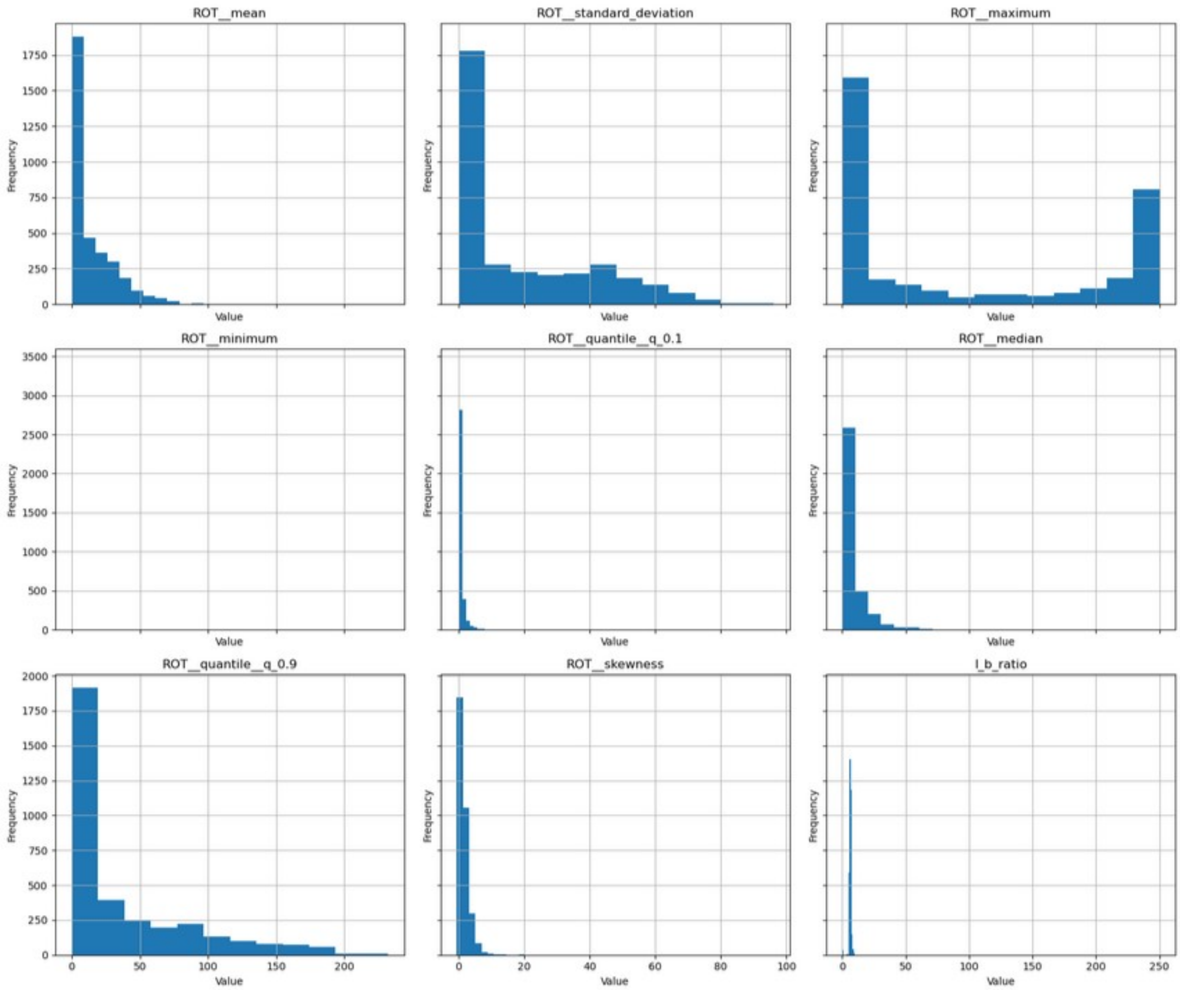

Figure G.4: Histrogram of ship motion features: ROT and L/B ratio, with trips of 1 hour

H
Sudden changes in speed

The standard deviation of SOG provides insight into sudden changes in speed. Figure H.2 shows a high standard deviation of SOG compared to the average value for this feature.

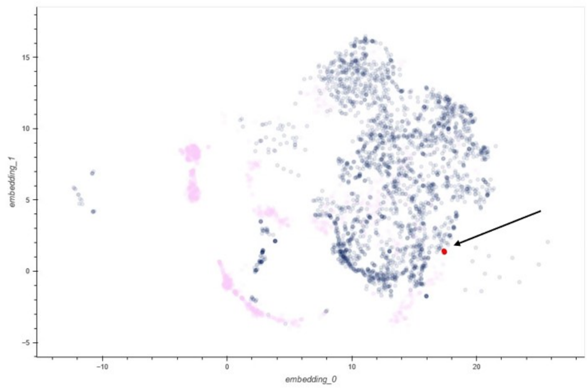

Figure H.1: Selected group for sudden change of speed: embedding

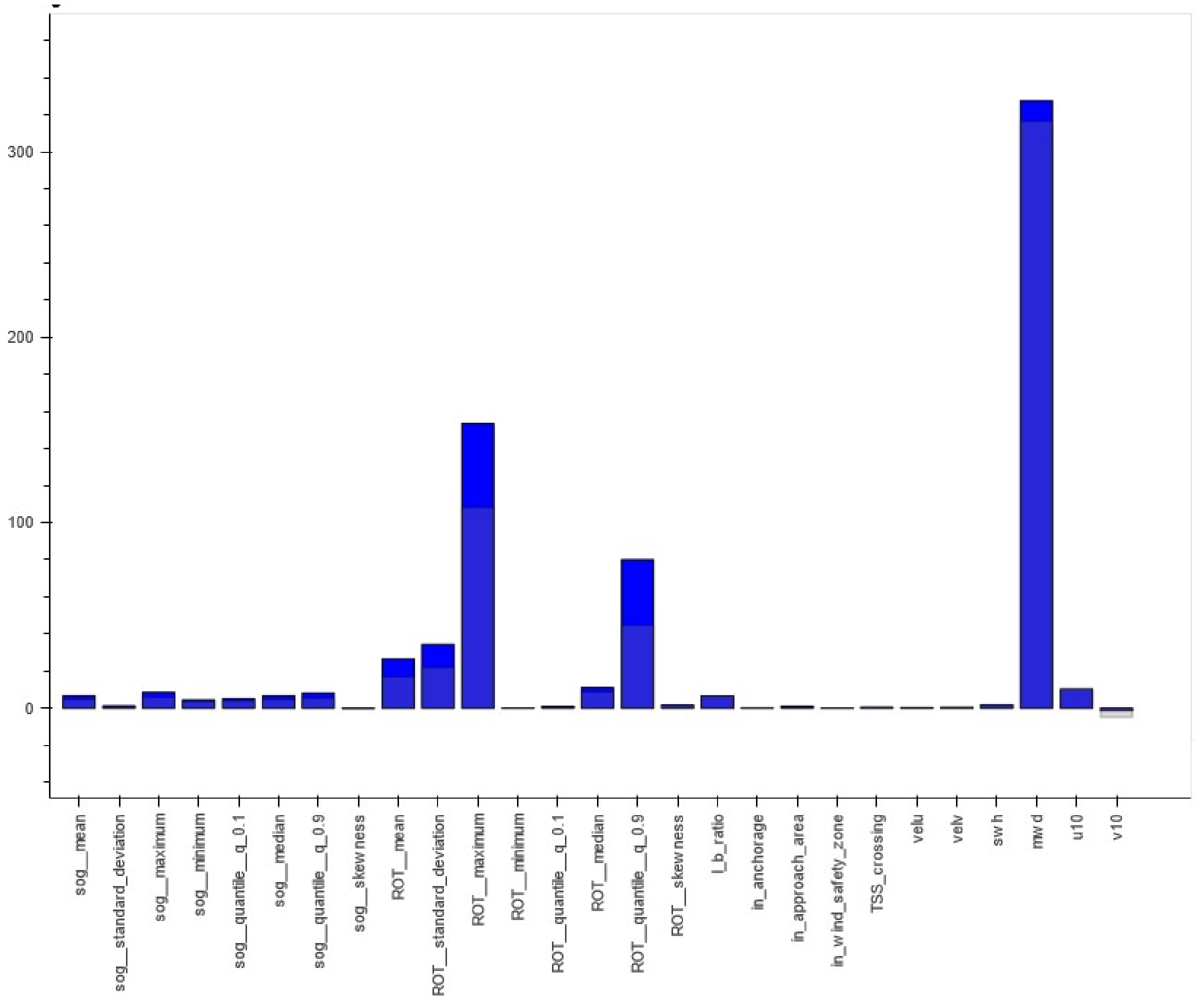

Figure H.2: Selected group for sudden change of speed: feature importance

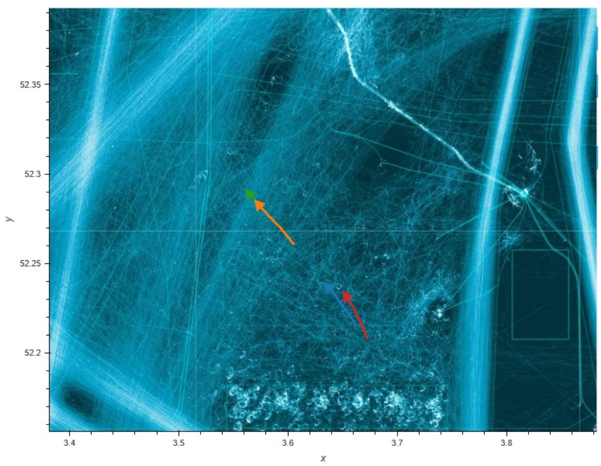

Figure H.3: Selected group for sudden change of speed: trajectories