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Multi-perspective nautical safety risk assessment of allisions with offshore wind parks

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ABSTRACT

The increasing amount of activities at sea, including the development of offshore wind parks, result in a more confined space for shipping, requiring the assessment of risk changes regarding nautical safety and the design of potential mitigation measures. The main contribution of this paper is the transparent evaluation of allision probabilities, based on an event-based approach. This enables a structural consideration of conditional probabilities, and supports uniting quantitative and qualitative analyses. The event-based approach allows evaluating the outcomes from various perspectives: scales, conditions, behaviour and dependencies. The analysis outcomes are represented in a concept called "event table", from which these perspectives can be extracted. Consequently, from this single data structure, insights can be gained ranging from spatial variations of the risk (highly detailed or global patterns), to detailed distinction between the most important influencing factors (varying from vessel type to environmental condition). It is furthermore possible to switch between wind-park specific risks and assessment of operational and strategic risk-mitigating measures for the entire area. The core feature of incorporating multiple perspectives not only allows various views on the safety risks, providing a better understanding of the most important contributing factors, as well as effectiveness of intervention measures. Our analysis shows the added value of additional distance between shipping lanes and wind parks in the spatial design, and we demonstrate how our multi-perspective approach supports the strategic and operational decisions around the availability and deployment of emergency response vessels.

1. Introduction

During a storm in January 2022, dry-bulk vessel Julietta D. suffered from a mooring system failure, sending the vessel adrift. Subsequently, it caused damage to another vessel, a platform under construction, and a wind turbine foundation. For decades, the North Sea has been an area of intense and multipurpose use, ranging from commercial shipping, fishing, and recreational activities, to areas for military training, nature reserves, oil and gas production, and sand extraction. On top of that, political ambitions express to extend the offshore wind capacity drastically, targeting 300 GW of offshore wind for the European Union (EU) in 2050 (European Commission, 2019). In Dutch territorial waters, an offshore wind capacity of 70 GW is planned for 2050 (Dutch Ministry of Infrastructure and Water Management, 2022). This results in an even higher intensity use, with closer interactions between shipping activities and offshore infrastructure in particular, having the potential to drastically impact the nautical safety (Duursma et al., 2019).

Despite the changing spatial design of the North Sea, the aim of the Dutch government is to preserve the current nautical safety level (Dutch Ministry of Infrastructure and Water Management, 2022; Minister of Infrastructure and Water Management, 2020b,a). For this purpose, an environmental impact assessment is a mandatory part of the site awarding procedure, which includes a nautical safety and risk assessment (Minister of Infrastructure and Water Management, 2020b). Furthermore, an investigation was launched about the effects of constructed and planned wind farms on shipping safety and mitigation measures, following the Formal Safety Assessment (FSA) principles by the International Maritime Organisation (IMO) (Maritime Safety Committee (MSC), 2018). The study concluded that "within realistic

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possibilities, none of the assessed measures can both individually or combined maintain shipping safety at the current level" (Duursma et al., 2019), calling for further research.

Two important challenges in managing nautical safety risks are the absence of a clearly defined target for nautical safety risks and a poor transparency of the assessments (Rawson and Brito, 2022). Regarding the definition of a risk target, the Dutch Safety Board (2024), in their investigation that was launched in response to the incident with the Julietta D., concluded that the "limited understanding of the level of risk and the lack of a realistic safety objective mean that shipping safety cannot at present be weighed up properly as part of the decision-making process". Likewise, Rawson and Brito (2022) address the lack of guidance by the FSA on acceptable navigation impacts that decision makers can use (Kontovas and Psaraftis, 2009) and the lack of a benchmark for Navigation Risk Assessment (NRA) in United Kingdom (UK)-waters.

The latter challenge has been addressed (Ellis et al., 2008; Goerlandt and Montewka, 2015; Čorić et al., 2021). Ellis et al. (2008) found significantly different return periods for powered and drifting collisions between various collision modelling approaches. According to Goerlandt and Kujala (2014), who compared multiple ship–ship collision approaches, the differences lead to concerns about the validity of the methods. Uncertainties around the assumptions made in the models were found to be an important cause for the large differences (Ellis et al., 2008). Moreover, Goerlandt and Montewka (2015) conclude that the involved uncertainties are not specifically or adequately discussed in maritime risk analyses. Hassel et al. (2021) therefore aimed to develop a more transparent risk model for propelled allisions to improve stakeholder's understanding of the mechanisms behind the calculations. Antão et al. (2023) assessed ship collision risk influencing factors from worldwide accident and fleet data, and emphasise the need for integration of "dynamic risk factors such as the local environment, weather, and navigation conditions". Despite this, the effect of environmental conditions on nautical safety risks are mostly neglected.

Risk models mostly express risk as the combined probabilities and consequences of scenarios (Kaplan and Garrick, 1981). How to incorporate uncertainties within this concept has been discussed by Aven (2010), starting from a distinction between two interpretations of probability (Bedford and Cooke, 2001): the relative frequency interpretation, whereby a probability distribution of an event to occur is estimated based on finite sample data, and the Bayesian perspective, with probability as a (subjective) measure of uncertainty based on background knowledge. For example, the probability of anchor failure under specific conditions can be determined based on historical event data, or based on experts relying on their subject knowledge. Hence, the degree of uncertainty is respectively driven by the approach and assumptions of the probability calculation, or by the knowledge of the expert.

Currently, in most risk models on nautical safety, the uncertainties are hidden in the probabilities, making it difficult for decision makers to design effective mitigation measures or to take action in case of large uncertainties combined with potentially large consequences. Aven (2010) proposes to explicitly reveal the uncertainties through a more qualitative approach. However, practically implementing this is challenging. Regarding the Dutch North Sea shipping risk assessments, the Dutch Safety Board (2024) found that even if an analysis includes a qualitative component, it was considered isolated from the quantitative analysis, limiting its added value. Considering the above, nautical safety risk assessments currently lack a structured approach that facilitates a transparent consideration of probabilities and associated uncertainties, combining quantitative and qualitative analysis and keeping track of the background knowledge. For identifying and designing effective mitigation measures, it is moreover required to gain an understanding of the conditional probabilities, i.e., which scenarios have the highest probability of an event and how likely are these scenarios to occur? In this view, Chen et al. (2019) highlight the opportunities offered by a strong relationship between risk analysis for individual ships and a macroscopic perspective, to come to better understandings of risks and potentially successful mitigation measures. Xiao et al. (2022) also recommend moving towards combined traffic level and individual-ship level approaches.

We address these issues by making use of an event table (van der Werff et al., 2024a): a concept facilitating scenario-based probability estimates to be coupled to qualitative expressions about their uncertainties as well as uncertainties on making successful interventions. We focus on drifting vessels, i.e., vessels that are Not Under Command (NUC) due to for example engine failure, a blackout, or mooring system failure. We evaluate the risk of colliding with offshore infrastructure like wind parks and platforms, referred to as *allision*, as opposed to *collision* which is between ships mutually. Despite the fact that there is a difference between collisions and allisions, the approach towards determining the associated risks is very similar.

Hereby, most existing approaches (Spouge, 1991; Koldenhof et al., 2010; Bandas et al., 2020; Kim et al., 2021) roughly distinguish between geometric probability, being the probability that two vessels are in a position with a potential to collide, and causation probability, being human, technical or organisational factors that can lead to an incident (Fujii and Shiobara, 1971). Although these approaches break down risk into several components, it is not clear which scenarios are considered exactly, and what the related assumptions are. The aim of this study is to enhance transparency by connecting (quantitative) probabilities to root-level scenarios. Hereby, we explicitly keep track of the associated assumptions. We consider this root level to be at the expected drift behaviour of individual vessels. Eppenga (2024) showed how aleatory probabilities could be determined by evaluating drift paths of an individual vessel under specified conditions and aggregating them into a spatial probability distribution.

The main contribution of this paper is the transparent evaluation of allision probabilities, whereby an event-based approach is followed, that enables uniting quantitative and qualitative analyses, and improves them by considering conditional probabilities in a structured way. We furthermore show that we can couple this to mitigation measures, and we demonstrate this by assessing the effectiveness of different operational strategies for ERTVs. This emphasises that the related risk-mitigating decision making requires viewing from different perspectives, ranging from spatial variations of the risk, to detailed distinction between the most important risk-influencing factors, for example, distinguishing between multiple environmental scenarios, and identifying vessel-type related behaviour contributing to high risks.

2. Materials and methods

2.1. Allision probability approach

Fujii and Shiobara (1971) defined the probability of a collision to be the product of the geometric probability and the causation probability. This approach is also used to determine the probability of a ship–object collision, e.g., allision (P_{allision}). Hereby, the geometric probability indicates the probability of a vessel being present at a particular location ($P(L)$), often evaluated using Automatic Identification System (AIS) data (Spouge, 1991; Koldenhof et al., 2010; Bandas et al., 2020; Kim et al., 2021). Spouge (1991) defined the causation probability as the combined probabilities to get adrift P_{adrift} (for example, due to engine failure), to drift in an unfavourable direction $P_{\text{unfav direction}}$ (for example, into a wind park), and to be unsuccessful in intervening $P_{\text{no interv.}}$, either externally (for example, towing assistance) or by own measures (for example, repairing the engine). This results in the following expression for the allision probability:

$$P_{\text{allision}} = P_{\text{geometric}} \cdot P_{\text{causation}} \tag{1}$$

$$P_{\text{geometry}} = P(L) \tag{1a}$$

$$P_{\text{causation}} = P_{\text{adrift}} \cdot P_{\text{unfav direction}} \cdot P_{\text{no interv.}} \tag{1b}$$

The heavy reliance on assumptions combined with the lack of transparency on their incorporation in the existing approaches to calculate allision risks are an important cause for the large differences in outcomes (Ellis et al., 2008). Therefore, Eppenga (2024) investigated the drift paths of a NUC-vessel under various conditions, to improve the understanding of the contributing factors to the probability that a vessel allides with offshore infrastructure, as captured by $P_{\text{unfav direction}}$ in Eq. (1). Based on a comparative study between various drift trajectory models Eppenga identified the open-source *OpenDrift* application (Dagestad et al., 2018a) as a suitable approach for the evaluation of vessel drift paths, which will be applied in this study as well. The application contains modules for evaluation of the propagation of various types of elements in space, by considering multiple sources of external forcing (Dagestad et al., 2018b). The *ShipDrift* module serves particularly for predicting the drift trajectories of vessels over 30 metres of length, explicitly incorporating the effect of waves, based on Sørgård and Vada (2011).

The vessel, defined by its length, width, draught and height, is in the basis assumed to move with the current, and relatively to this driven by other external forces, being wind and waves. Wind and current are expressed by the u- and v-velocity components in the horizontal plane. The waves are defined by the significant wave height and mean period, and the direction is expressed by a Stokes drift velocity vector, whereby the magnitude is determined based on the wave height. Geometry-specific drag coefficients are used to translate the environmental conditions into the external forcing on the ship. Based on the environmental and vessel-related input, *OpenDrift* derives a deterministic drift path. Randomness is added through implementation of a random starting orientation of the vessel and a probability of jibing during the drift run. Furthermore a horizontal diffusivity is applied, jointly resulting in varying drift paths for multiple repetitions of the same input conditions (seed variations). Hence, for a single vessel, in one specific environment, multiple simulation seed variations are conducted, resulting in multiple drift paths. Subsequently, the probability of drifting through a wind park (for a single vessel, in one specific environment) is determined by assessing how many of the total drift path realisations cross a wind park boundary.

2.2. OpenDrift validation

Since the supporting calibration documents (Sørgård and Vada, 2011) are not publicly available, Eppenga (2024) conducted a case study whereby the drift event of the Julietta D. in 2022 was reconstructed using *OpenDrift*, based on the in-situ environmental conditions during the incident. Refer to Fig. 1, indicating the actual drift path of Julietta D. in black, and the *OpenDrift* drift path realisations in green. The bold line indicates the mean coordinates per time step. Simulation outcomes were found to be in good agreement with the actual drift path of the vessel, as can be seen in Fig. 1(a). Furthermore, it was demonstrated that incorporation of the temporal variation of the tidal currents is required to correctly model the vessel drift path for the entire time span. Especially when analysing drift paths in close vicinity of wind parks, it is important that the drift path should be correct over the entire time span (including the first couple of time steps), instead of an overall correct direction with large deviations over the track.

2.3. Data sources

The data sources used in this study are presented here:

North Sea geometries Geometry coordinates for spatial features at the North Sea provided exact locations of shipping lanes, anchorage areas and wind parks (Kennis- en Exploitatiecentrum Officiële Overheidspublicaties (KOOP), 2024). Refer to Fig. 2, wherein these features are presented.

AIS data Following the IMO directive adopted in 2000, larger vessels are required to share data on their position, speed, vessel properties and identity for nautical safety purposes (Maritime Safety Committee, 1998). Historic logs of AIS data can be used to study vessel behaviour. For this study, anonymised AIS data was used. The evaluated area was the Dutch North Sea coastal area between Den Helder (52.95 degrees North) and Vlissingen (51.45 degrees North). The boundary of the area is indicated by the green dotted line in Fig. 2 and a density map based on the AIS data for the evaluated area is presented in Fig. 3. We used data of January, April, July and October 2019, which are considered representative for the nautical traffic analysis for the entire year. The data were made available by the Dutch Coastguard and Rijkswaterstaat, the executive agency of the Dutch Ministry of Infrastructure and Water Management, that collects this data for the Dutch territory. The data were filtered, keeping only data points explicitly indicating a vessel of the type passenger, cargo, or tanker, indicated by a "vesseltype" field of 60–69, 70–79, and 80–89, respectively. Furthermore, data points with both unknown vessel length and width were removed.

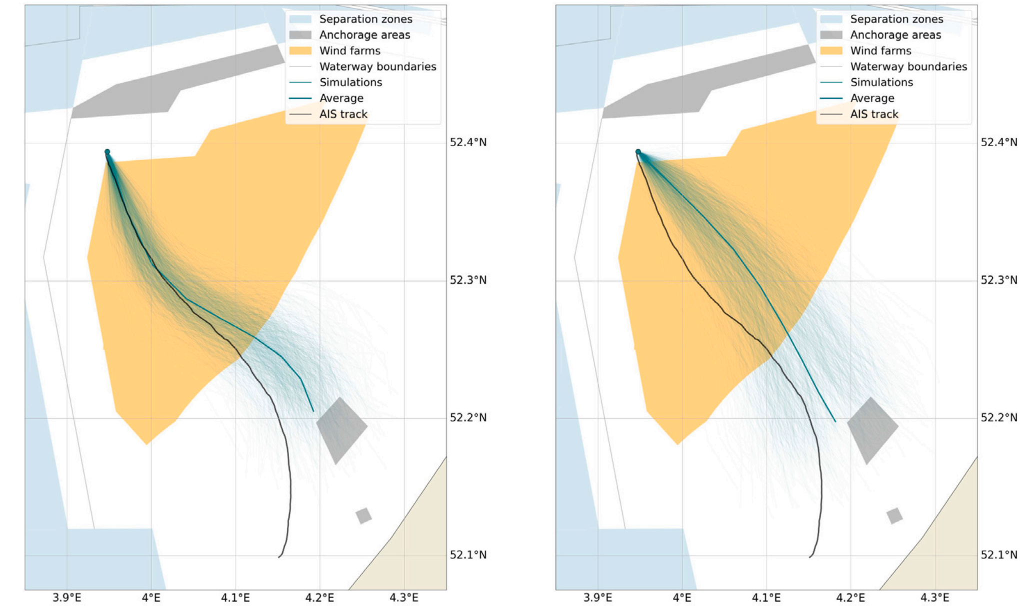
ERA5 data ERA5 (Hersbach et al., 2023) is the fifth generation reanalysis for the global climate and weather made by the European Centre for Medium-Range Weather Forecasts (ECMWF), combining model data with global observations. The environmental data encompasses hourly wave height, period and direction data, and hourly wind velocity and direction data. The environmental data has a spatial resolution of 0.5-by-0.5 degrees. For all locations in the evaluated area, the closest metocean data points were included. Ten years (2014–2023) of data were evaluated.

Current data Only tidal currents were considered (no wind-driven currents were included). The tidal currents were retrieved from the Global Tide and Surge Model (GTSM) and SWAN model. We selected one time window as representative for the variety of cycles that occur in the area, starting on June 24th, 2021 at 3.00 h. Northerly and Easterly velocity components were used in the analysis.

2.4. Conceptual model for allision risks

In this section, the conceptual model is outlined for the evaluation of the allision probabilities in an entire area of the North Sea, making use of simulated drift paths. Besides connecting vessel-specific drift paths to an integrated allision probability, this conceptual model should keep track of the background information to obtain the desired transparency regarding incorporated assumptions and effectiveness of potential improvement measures. Having various perspectives on a problem is essential to understand the most effective solutions, and on where and how to implement them. Aiming to improve the understanding of systems with high complexity, van der Werff et al. (2024a) developed a framework to express analysis objectives from four distinguished perspectives: *scales*, *conditions*, *behaviour*, and *dependencies*, and to translate them into corresponding requirements for a data-structure concept: an *event table*. Hereby, the connection with detail level events (the drift paths, in this case) is explicitly maintained.

Table 1 presents the framework. The fundamental-component requirements prescribe how distinct events are defined, basically characterising the highest level of detail in the table, represented by its rows. The other requirements prescribe the additional information that is required for each event, stored as attributes in the columns of the table. An event table is unique due to its capability to combine spatial and temporal data (using moving-features principles, see Asahara et al., 2015) with an event-based structure (using process-mining principles, see van der Aalst, 2012).



(a) Simulations based on in-situ environmental conditions including the temporal variations of the tidal current

(b) Simulations based on in-situ environmental conditions with exception of the tidal current

Fig. 1. Simulated drift paths for Julietta D. with *OpenDrift* (Eppenga, 2024).

Table 1
Multi-perspective framework for defining analysis objectives and translating them into corresponding concept requirements (van der Werff et al., 2024a).

Perspective	Requirement	
Scales - The 'where' and 'when' of the performance, uncovering spatial patterns and temporal variations	Fundamental components	The highest level of detail in time (seconds, hours, months, etc.) The highest level of detail in space
	Aggregation means	For deriving time aggregates (hours, days, weeks, months, etc.) For deriving spatial aggregates
Conditions - Understand how system performance is connected to its underlying processes and their environment	Fundamental components	The highest level of detail of environmental and process description
	Influencing factors	Attributes that indicate influencing factors, and that couple them to performance
Behaviour - How the performance of the system is influenced by the behaviour of individual agents or collectives	Fundamental components	The highest detail level of individual agent or process to keep track of
	Activity sequence	Means to track the sequence of activities performed by the agent
Dependencies - Identify causal relationships, critical paths, and sensitivities within the entire system	Initiations	Dependency of an event on (an)other event(s)

The framework helps designing a concept considering the definition of a scenario, and the additional required information to obtain a comprehensive understanding of the risks from various perspectives. The first aspect, defining the risk scenarios (Kaplan and Garrick, 1981) that should be considered, corresponds to the fundamental-component requirements in the event table (its rows). Therefore, we use the term *event* to indicate a specific situation to which a probability of occurrence and consequences can be assigned, instead of *scenario*. The second aspect regards calculating event-based probabilities, and holding on to the necessary background knowledge, stored as attributes in the columns. By using the event-table concept, we ensure that the integrated probabilities can be determined, that various perspectives can be extracted, and that background information can be explored. Table 2 presents how the framework (van der Werff et al., 2024a) is used to define the event table requirements for allision risks, distinguishing between the four perspectives:

Scales To evaluate spatial patterns and temporal trends, requires defining the highest detail levels (fundamental components) in space and time, and having a hierarchic structure that allows the probabilities to be quantified in space. Given the two-dimensional appearance of shipping patterns, a spatial grid with a cell size of approximately 1 km^2 was used for this. Analyses are at annual basis.

Conditions This considers the influence of environmental conditions on the allision risk, requiring environmental data on all potentially important conditions. To distinguish between environmental influences, sets of environmental conditions are treated as fundamental components, whereby a set is defined by wave height, period, and direction, wind speed and direction, and surface current speed and direction.

Behaviour To determine allision probabilities, requires understanding the response of a drifting vessel to its circumstances. We describe

Table 2
Multi-perspective framework for defining analysis objectives and corresponding concept requirements for the analysis of vessel-object allision risks.

Perspective	Requirement	
Scales - Spatial patterns of vessel-object allision risk levels and temporal trends	Fundamental components	Area of ∼1 km^2 Year
	Aggregation means	Spatial grid
Conditions - Determine the influence of the environmental conditions on the probability levels	Fundamental components	Wave height/period/direction, wind speed/direction, current speed/direction
	Influencing factors	Keep connection between probabilities and corresponding background knowledge (quantitative and qualitative)
Behaviour - Understand vessel response to varying environmental conditions	Fundamental components	Hourly response for distinct vessel types/sizes
	Activity sequence	Track hourly sequence of events during drifting
Dependencies - To construct drifting-time dependent course of events and couple this to external intervention measures	Initiations	Establish probability of timely arrival of ERTV and consequential residual risk

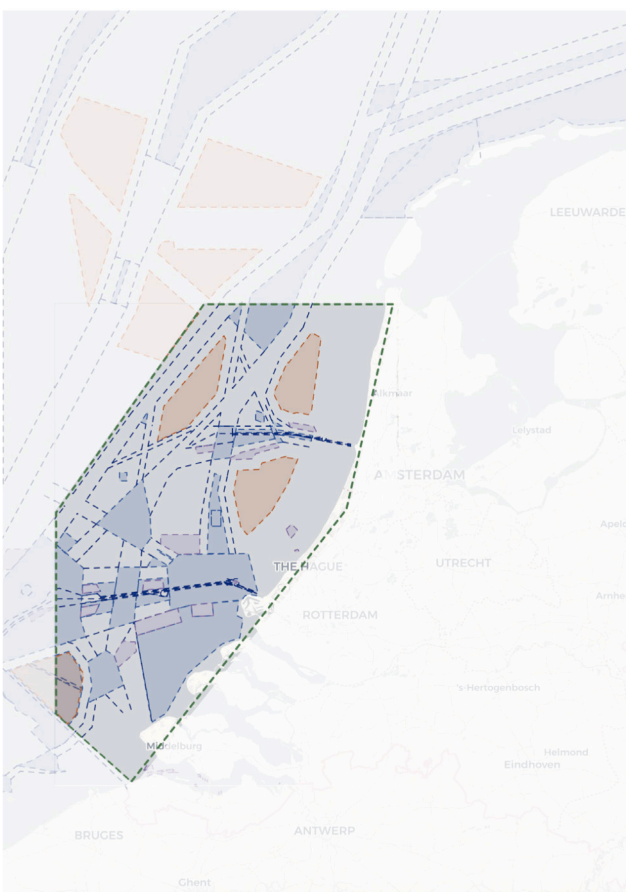


Fig. 2. Traffic separation scheme (blue filled, with traffic lanes blue dotted), anchor areas (purple filled), and wind parks (red filled) in the considered area (green boundary dotted) at the Dutch North Sea, excluded area shaded.

Fig. 3. Considered area (non-shaded in Fig. 2) with densities derived from AIS data projected on the constructed grid whereby the 1-by-1 km cells were divided at the boundaries of different utilisation areas.

this by travelling speed and direction over hourly time intervals, to derive the drifting time before entering a wind park. We want to account for different behaviour expected for different vessel types and dimensions.

Dependencies We use this perspective to link the crossing of a wind park to an entire drift track. When evaluating only specific coordinates of the track after exiting the wind park, hence, coordinates that lay outside the park, it should be known that the track has crossed through it. As these samples are captured by different events in the table, we need to explicitly link them.

The above considerations determine the design of the event table. In light of the first purpose (define the events, hence, design the rows of the table), we gather the fundamental components. Consequently, each event is defined by a unique combination of *year* and *km*^{2} *area* (scales perspective), *environmental conditions set* (conditions perspective), and *vessel category* (behaviour perspective). The combining of all possible combinations of fundamental components can be represented by a probability tree, refer to Fig. 4. For an evaluated year (expressed by S_{year}), the drift paths of all considered vessel types (S_{vessel}) subject to all potential environmental conditions (S_{env}) are determined. Finally, the drift paths are transposed to each location (S_{loc}), represented by the outer branches. Hence, the resulting event table is presented on the right-hand side of Fig. 4. The descriptions of each of the fundamental components are described in more detail in the remainder of this section. The calculation approach is explained in Section 2.5.3. Events with a zero probability of occurrence are not included in the table.

For the second purpose (attributes to be stored in the table columns), besides the probability components, it is required to store information about the environmental conditions, the vessel, the location, as well as the drift paths on an hourly basis. This is also indicated in Fig. 4. Section 2.5 provides further detail.

A unique event is defined by a unique combination of the fundamental components *year*, *location*, *environmental conditions set*, and *vessel category*, as described below. Their descriptions reflect the level of detail that is stored in a single row in the event table.

Year Following from the scales perspective, the specified temporal fundamental component was a year. Due to the availability of AIS data only for one year, vessel densities could only be determined for 2019.

Square kilometre area This also follows from the scales perspective. A spatial grid was used to distinguish between locations with cell dimensions of 1-by-1 km. The cells were divided at the boundaries of different utilisation areas, i.e., at the shipping lanes, anchor areas, and wind farm areas. The grid is presented in Fig. 3, whereby for each cell, the shipping density was determined based on AIS data (van der Werff et al., 2024b), thereby clearly indicating different cell shipping densities for shipping lanes and anchorage areas, and other areas.

Environment The conditions perspective prescribed distinction between environmental conditions. We used the parameters wave height, wave period, wave direction, wind speed and wind direction from ERA5 data. For each parameter, we considered the entire range of occurrences in the considered area, and divided them into parameter-specific bins, refer to Table 3. An exception is the wave period, which was assumed related to the wave height. The size of the bins was chosen based on a sensitivity study of the drift path analysis, indicating among others a higher sensitivity to the wind speed than to the wave height, resulting in a smaller number of bins for the latter. Furthermore, the sensitivity of the drift path to the misalignment angle between the wind and the waves was limited, driving the choice for using only three bins, as indicated in Table 3. For the current profile, we considered 4 different starting times in a fixed, representative, tidal cycle, at 3 h intervals. Hence, the current velocity and direction varied over time in the drift simulations. All combinations of environmental parameter bins would theoretically result in 5184 environmental scenarios, however, accounting for only those scenarios that actually occurred in the 10-year data set reduces the number of environmental scenarios to 1784.

Vessel type The fundamental component related to the behaviour perspective is the vessel type. We distinguished four main types, being dry bulk, container, and passenger vessels, and tankers. For each type, a number of size categories were defined, refer to Table 4. The reason for distinguishing vessel types apart from sizes, is the different dimension ratios that may affect the drift path of the vessel. For example, compared to bulk vessels and tankers, a (loaded) container vessel has a larger wind area, and compared to that, a cruise ship has a much smaller draught. Sensitivity analyses for the drift paths have also been executed for the various vessels.

2.5. Event-based allision probabilities

Each row in the event table represents a unique combination of fundamental components (year, location, environmental conditions, and vessel category as defined in Section 2.4). The probability of an event equals the probability of that unique combination of year, location, environmental conditions, and vessel category. The causation probability, subsequently, is the probability of an allision in case of that event. Note that the original definition of an allision (Eq. (1)) multiplies P_{geometry} with $P_{\text{causation}}$, and our definition of an allision (Eq. (2)) instead multiplies P_{event} with $P_{\text{causation}}$. The difference between P_{geometry} and P_{event} is that P_{geometry} only considers a location probability $P(L)$, while P_{event} considers probabilities of location $P(L)$, vessel type $P(V)$, and environment $P(E)$.

$$P_{\text{allision}} = P_{\text{event}} \cdot P_{\text{causation}} \tag{2}$$

$$P_{\text{event}} = P(L) \cdot P(V) \cdot P(E) \tag{2a}$$

$$P_{\text{causation}} = P_{\text{adrift}} \cdot P_{\text{unfav direction}} \cdot P_{\text{no interv.}} \tag{2b}$$

Each of these probabilities, as well as intermediate results to determine them, are stored in attribute columns of the event table.

2.5.1. Event probability

This section considers the approach for determining the event probability, as defined in Eq. (2a). The location probability was determined by evaluating the number of vessel crossings for each cell in the grid, using AIS data. This was done by assigning each AIS sample to a cell in the grid. Samples for one vessel, within one cell, with time stamps of less than an hour apart were jointly counted as one crossing. The probability $P(L)$ was incorporated as the number of crossings per hour. For each cell, the vessel type probability was determined by assigning the vessel category to each vessel crossing. The probability $P(V)$ was incorporated as the fraction of the total number of crossings that were made by a particular vessel category for that cell. Fig. 5 presents the combined location and vessel type probability for three tanker categories. The environmental probability was determined by evaluating all 3-hour hindcast samples for the metocean sample location nearest to the evaluated cell. The probability $P(E)$ was incorporated as the fraction of all samples that corresponded to a particular environmental scenario. Fig. 6 presents the probabilities of occurrence for all wind speed-direction combination (Fig. 6(a)) and for all combinations of wave height and wave direction relative to the wind direction (Fig. 6(b)). Note that both $P(V)$ and $P(E)$ are location specific.

2.5.2. Getting-adrift probability

This probability considers the probability that a vessel becomes NUC, and starts drifting. In this study, we only took into account the probability of a mooring failure (if the utility of the cell (L_{utility}) in which the vessel is located is an anchorage) and the probability of an engine failure (if the vessel is anywhere outside the anchor areas). Due to the design of the spatial grid, whether a vessel was in an anchorage area could be determined based on the grid cell it was located in. In case of an engine failure, we assigned equal failure probabilities for varying vessel categories and environmental conditions, and in case of a mooring failure, we assigned a wind speed dependent failure probability (Ellis et al., 2008). Refer to Eq. (3). The event-based approach facilitates more detailed conditional probability values based on expert opinions or extensive statistical data, if available.

$$P_{\text{adrift}} = \begin{cases} f(v_{\text{wind}}), & \text{if } L_{\text{utility}} = \text{“anchorage”} \\ 0.00025, & \text{otherwise} \end{cases} \tag{3}$$

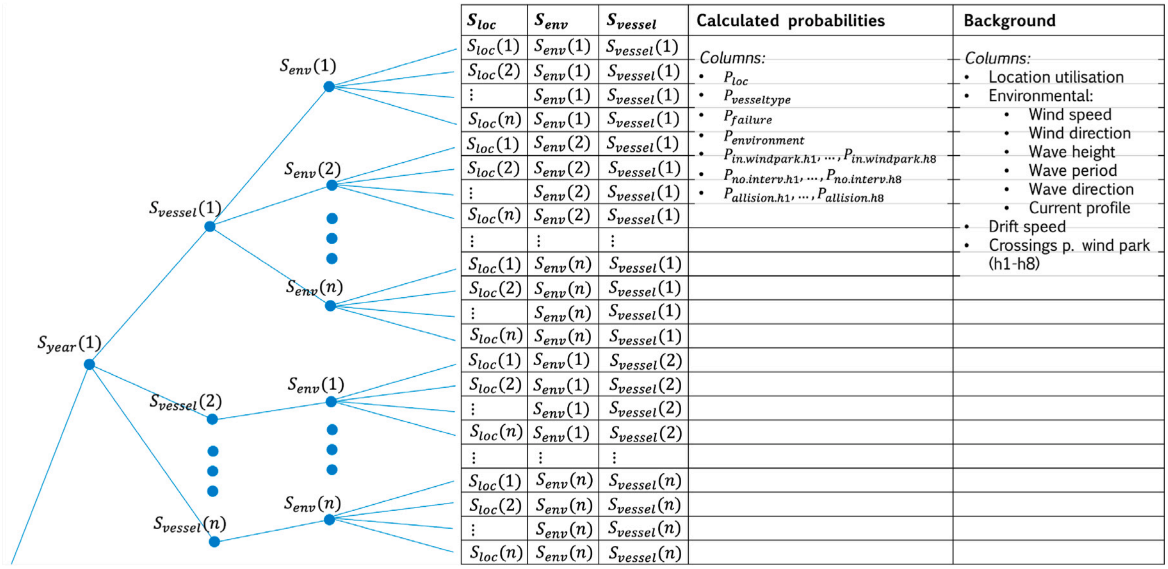


Fig. 4. Construction of the event table by considering all unique scenarios.

Table 3
Bins of environmental parameters to construct environmental scenarios.

Env. parameter	Nr bins	Bin size	Description
Wind direction	8	45 degrees	Bin medians equal compass directions (N, NE, E, etc.)
Wind speed	9	2.5 m/s	Upper bin includes all speeds > 20 m/s)
Relative wave direction	3	–	Aligned: [−45, 45] deg, misaligned: [−180, −45] and [45, 180] deg (w.r.t. wind dir.)
Wave height	6	1 m	Lower bin has range [0, 1.2], upper bin includes all heights > 5.2 m
Current speed/direction	4	3 h	Implemented through varying start times in tidal cycle

Table 4
Vessel types and categories considered in the event table, with indicated length, breadth and draught dimensions (LxBxT) and overall height (distance from keel to height above water) H.

Cat	Bulk	Tanker	Container	Cruise
1	Handysize 182 × 28 × 15 H:15	Coastal 205 × 29 × 24 H:24	Early 210 × 20 × 10 H:23	1982-generation 215 × 29 × 7 H:42
2	Panamax 225 × 32 × 12 H:19.5	Aframax 245 × 34 × 20 H:30	Panamax 290 × 32 × 13 H:36	1996-generation 280 × 32 × 8 H:55
3	Capesize 289 × 45 × 17 H:24	Suezmax 285 × 45 × 23 H:34	Post-Panamax 340 × 43 × 15 H:39	2006-generation 339 × 39 × 9 H:68
4		VLCC 330 × 55 × 28 H:42	VLCS 397 × 56 × 16 H:47	2009-generation 360 × 47 × 9 H:72
5		ULCC 415 × 63 × 35 H:52	ULCS 400 × 61 × 16 H:65	

2.5.3. Unfavourable drift direction probability

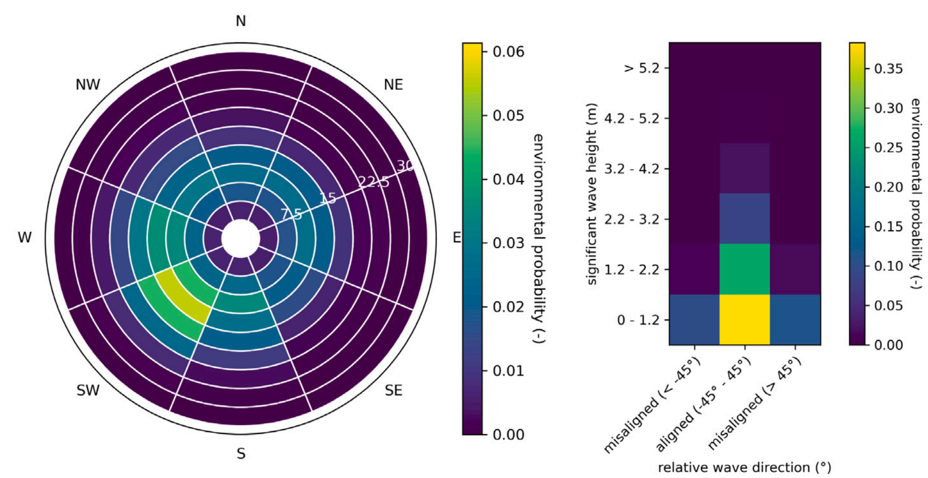
We consider an unfavourable drift direction to be a drift path that crosses a wind park. To determine the probability hereof, 300 drift path seed variations were calculated with *OpenDrift* for every unique combination of an environment and a vessel category. The resulting drift path coordinates, logged hourly over a time interval of 8 h, were translated to each cell in the grid, whereby the starting point of the drift matched the centroid of the cell. Subsequently, the drift path coordinates intersecting with the wind park polygon areas were identified. All coordinates in a single drift trajectory following a sample intersecting a wind park, were identified as positive. This is illustrated by Fig. 7. The probability of drifting into a wind park $P_{\text{unfav. direction}}$ was determined at hourly intervals by the fraction of the total number of seeds (e.g., 300) that was either in a wind park or on a trajectory that had already crossed a wind park.

2.5.4. Non-intervention probability

To make a successful intervention can entail many different measures, ranging from actions on board the vessel (repairing the engine or gear box, deploying the emergency anchor) to external actions (towing by an ERTV). The presented approach facilitates incorporation of any kind of intervention measure. For example, hourly probabilities of failure to repair the engine by the vessel crew, can be incorporated. Thereby, a higher drift velocity results in a lower probability of engine-repair before reaching a wind farm. However, in this study we only consider the external intervention by means of an ERTV, which demonstrates the capability of considering multiple deployment strategies and incorporation of operational choices and limitations. Hereby, we distinguish between vessel types when assuming the probability of a successful intervention. For most types, we assume a 100% success rate if the ERTV manages to reach the drifting vessel before entering a

(a) Geometric probability of Aframax tanker (b) Geometric probability of Suezmax tanker (c) Geometric probability of a VLCC

Fig. 5. Geometric probability for three tanker categories.



(a) Aggregated probability of occurrence for wind speeds and wind directions for the entire considered area (b) Aggregated probability of occurrence for wave heights and wave directions (relative to wind directions for the entire considered area

Fig. 6. Aggregated probability of occurrence for wind and wave conditions for the entire considered area.

wind park, hence, if the response time of the ERTV (e.g., the distance to the nearest ERTV, D_{ERTV}, divided by its speed v_{ERTV}), is smaller than the time until the drifting vessel crosses a wind park boundary $t_{(\text{drift in park})}$, refer to Eq. (4). Only for the largest vessel classes, being ULCC, VLCS, ULCS and 2009-type cruise ship, we assume a 0% success rate above Beaufort 7. Clearly, this assumption can be refined by specifying limiting weather conditions, limiting vessel displacements, limiting vessel wind areas, or combinations thereof.

$$P_{\text{no interv.}} = \begin{cases} 0, & \text{if } \dfrac{D_{\text{ERTV}}}{v_{\text{ERTV}}} \leq t_{(\text{drift in park})} \\ 0, & \text{if } v_{\text{wind}} > 17.2 \text{ and large vessel type} \\ 1, & \text{otherwise} \end{cases} \tag{4}$$

3. Results

The generated event table, based on the above definitions and occurrences, consists of 93,158,508 rows (hence, unique events) and 151 columns. The events are combinations of 7247 grid cell locations, 13 vessel types, and 1784 metocean conditions. From it, we can extract and evaluate the allision risks from various perspectives, as specified in Table 2. Moreover, because all outcomes can now be extracted from a single data structure, they can be used in a highly complementary way. In this section, multiple examples of extractions from the event table are presented, however, depending on the analysis, many other extractions may be made. Furthermore, as it will become clear, some visualisations do not necessarily consider one single perspective. For the first insights, regarding the scales, conditions and behaviour perspectives, we focus on the allision probability assuming there are no intervention measures in place, in order to investigate high-probability causes. To demonstrate how this can be done, we evaluate the overall, wind-park specific, and traffic-lane specific probabilities, each of them representing different considerations for decision making. The overall probabilities help exploring where the highest probabilities occur, and the general conditions that contribute the most to allision probabilities. Wind-park specific evaluation considers allision risks posed by vessels sailing anywhere around that park, whereas fairway-specific evaluation considers the likeliness that a vessel sailing a particular route, drifts into any nearby wind park. In the last part of this section (regarding dependencies), we will consider two ERTV deployment strategies to illustrate how their effectiveness can be evaluated using our approach.

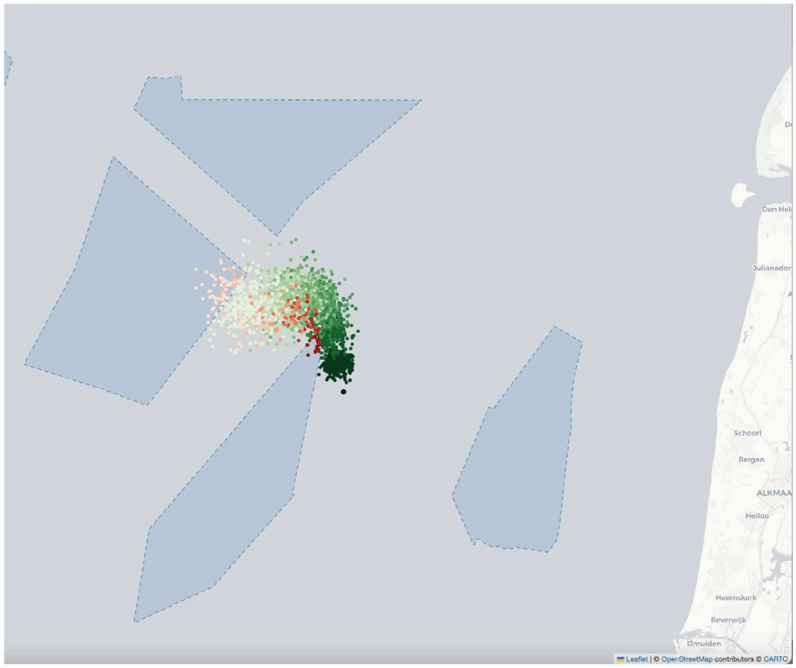
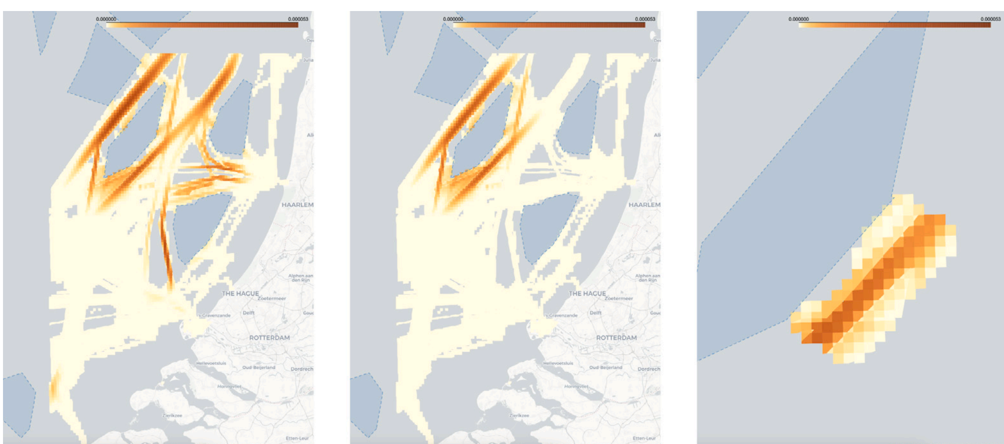


Fig. 7. Evaluation of 300 drift paths (for one vessel type, and one environmental condition set) generated with *OpenDrift* for crossing of wind park. Red markers indicate drift paths that cross or have crossed a wind park, colour shades indicate drift time (darkest shades for short drift times).



(a) Allision probabilities for all wind parks jointly (drift time 4 hours)

(b) Allision probabilities for one wind park, i.c. Hollandse Kust West (drift time 4 hours)

(c) Allision probabilities for a specific traffic lane section, i.c. Southeast of Hollandse Kust West (drift time 4 hours)

Fig. 8. Zooming in at various spatial scales to evaluate allision probabilities.

Scales The first objective, from a scale perspective, was to derive spatial patterns of the allision probabilities. Fig. 8 presents three spatial "zoom levels" of this perspective, whereby Fig. 8(a) indicates the allision probabilities after four hours, for all windparks in the entire area, for all vessel types. Fig. 8(b) presents only the allision probabilities for one particular wind park, Hollandse Kust West, and Fig. 8(c) presents a zoom-in for the traffic lane Southeast of the wind park Hollandse Kust West. These different views can typically be used by different stakeholders, where a wind park owner or operator may be more interested in the likeliness that a vessel drifts into a their particular wind park.

A state authority would be more interested in an integrated picture, showing the overall spatial distribution of the probabilities. From Fig. 8(c) it can be seen that the main traffic lane has the highest traffic densities, but that there are still vessels in the area between the traffic lane and the wind park. Fig. 8(a) shows the resulting allision probabilities from NUC-vessels in these areas. As expected, the highest probabilities occur in close vicinity of the wind parks. A lower traffic density reduces the allision probability. Furthermore, it can be observed that moving further away from the wind park decreases the allision probability. This is supported by Fig. 9, showing the aggregated allision probability for each grid cell, based on its distance to the nearest wind park. The peak corresponds to the high allision probability of traffic lanes nearby a wind park, at approximately 3.5 km distance. The range left of the peak are buffer zones between shipping lanes and wind park with less dense vessel traffic. To significantly reduce the allision probability, in the design of future wind parks, the distance between traffic lanes and a wind park should be increased by a factor of 1.5 to 2,

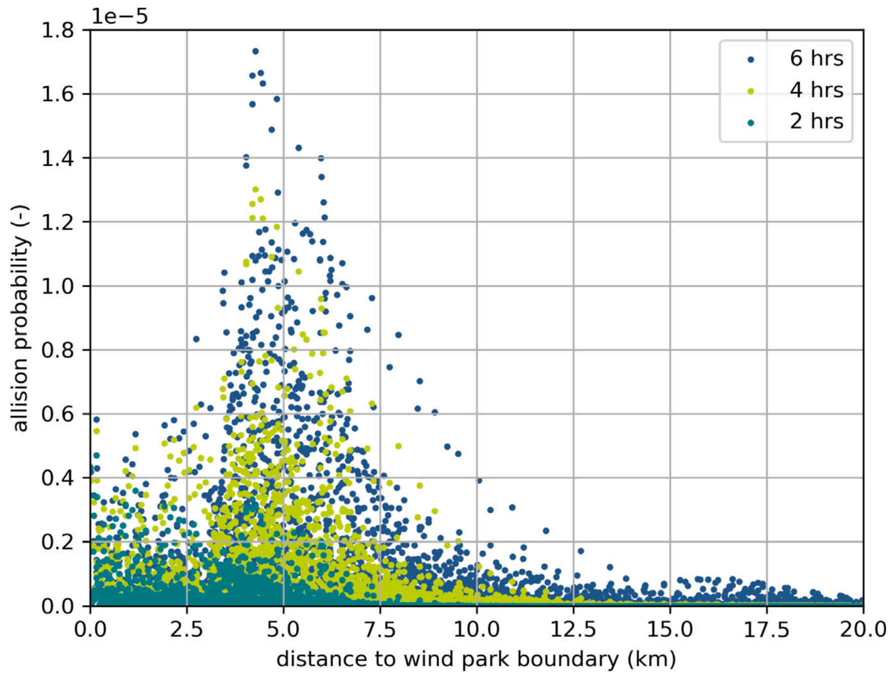


Fig. 9. Allision probability for cell centroid distance to nearest wind park boundary.

however, by creating Fig. 9 for specific areas, wind-park specific buffer-zone widths can be derived.

Conditions The second perspective, regarding conditions, aimed at understanding the influence of environmental conditions on the probability levels. By keeping track of all intermediate outcomes in the event table, a better understanding can be gained than purely by inspecting the contributions of environmental scenarios. We can now enrich our knowledge for the spatial patterns from Fig. 8, by extracting the contributing environmental conditions to these zoom levels. Fig. 10 presents the contribution of the range of wind directions to the allision probability, for the same scopes as in Fig. 8.

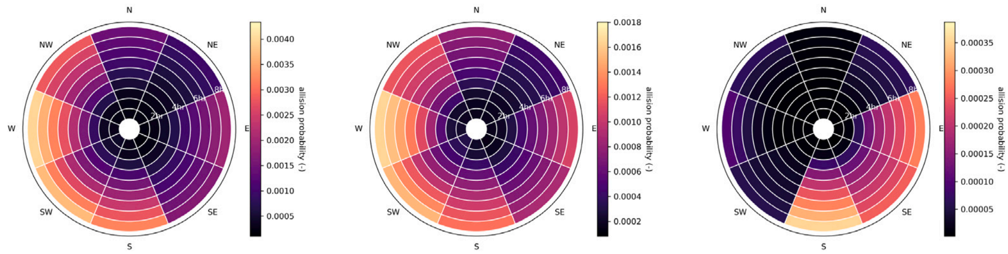
Based on Fig. 6(a) it is known that the highest probability of occurrence is for wind speeds around 7 m/s (4 Beaufort) and wind directions coming from the Southwest range. Furthermore, the wind speeds from this direction are generally also higher than from other directions, which can be seen from the smaller outer band of dark blue colours in the Southwest. Combined with the spatial design of the North Sea, with most traffic lanes in a North–South direction, and wind parks on the West and East sides, this results in the highest allision probabilities for Westerly and Southwesterly wind directions (Fig. 10(a)). The same is observed for the Hollandse Kust West wind park (Fig. 10(b)), as the traffic lanes are situated all around this park. For the traffic lane area in Fig. 10(c), Easterly to Southerly winds predominantly have the potential to cause allisions. The small probability for Westerly winds occurs because after a long drift, vessels may drift into the Hollandse Kust Noord wind park, East of the evaluated area.

Behaviour Furthermore, we can evaluate the allision probabilities for different vessel types, refer to Fig. 11. Similar to the environmental conditions, we can investigate how different vessel types contribute to the allision probability. Comparing Fig. 11(a) and Fig. 11(c) clearly shows that small bulk- and container vessels have a high allision probability due to their large presence. Furthermore, despite their occurrence rates being comparable to tankers, very- and ultra-large container vessels have a significantly larger probability of drifting into a wind park (see Fig. 11(b), which can be attributed to the large wind areas of container vessels.

Dependencies As part of the dependencies perspective, the aim was to evaluate the influence of external intervention measures on the allision probability. Fig. 12 presents visualisations of extractions of the event table that can support assessing them, based on all incorporated vessel types, wherein Fig. 12(a), Fig. 12(d) and Fig. 12(g) present the allision probabilities without the intervention of an ERTV for 2, 3, and 4 h of drifting, respectively. We considered two ERTV strategies: the first entailed stationing ERTVs in Rotterdam and in Den Helder (refer to Fig. 12(b), Fig. 12(e), and Fig. 12(h) for 2, 3, and 4 h of drifting, respectively), and the second entailed stationing ERTVs in IJmuiden and in Den Helder (refer to Fig. 12(c), Fig. 12(f), and Fig. 12(i) for 2, 3, and 4 h of drifting, respectively). The green circles mark the assumed range of the ERTVs after the considered drift time. From these maps, the residual probabilities for the two scenarios can be compared. It shows that the first strategy is more successful to reduce the allision probability in the Southern wind park (Borssele and Hollandse Kust Zuid), while the second strategy is more successful in reducing the allision probability around the Northerly wind parks (Hollandse Kust Noord and the East side of Hollandse Kust West). Currently, a constant, fixed sailing speed is assumed for both vessels, however, because the events distinguish between environmental conditions as well, a weather-dependent sailing speed could be implemented, and even a tidal-current dependency could be incorporated.

4. Comparison with other work

The results in the previous section highlight the different perspectives that can be used to evaluate allision risks at the North Sea. It is foremost meant to demonstrate the flexibility of such a way of approaching these risks, and potential measures. Therefore, some probability components have not been fully evaluated yet, such

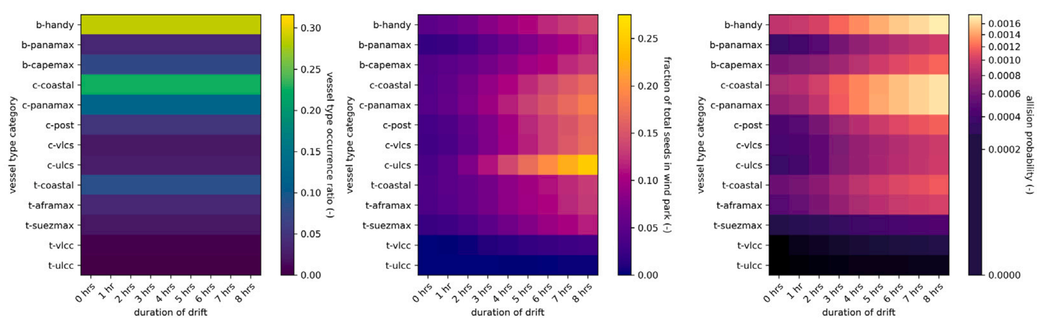


(a) Overall allision probability contributions by wind direction, for 0 to 8 hours of drifting (from center outward)

(b) Wind-park (Hollandse Kust West) specific allision probability contributions by wind direction, for 0 to 8 hours of drifting (from center outward)

(c) Area (Southeast of Hollandse Kust West) specific allision probability contributions by wind direction, for 0 to 8 hours of drifting (from center outward)

Fig. 10. Various spatial scales for evaluating allision probabilities.



(a) Occurrence probability of vessel type categories in the entire considered area

(b) Probability of drifting into a wind park for vessel type categories in the entire considered area

(c) Allision probability of vessel type categories in the entire considered area

Fig. 11. Probability of vessel type occurrence, conditional probability of drifting into a wind park, and allision probability without intervention measures, broken down by vessel type category.

as the self-repair and emergency-anchoring probability. Consequently, comparing with other works directly, is difficult. To demonstrate the novelty of our approach, we compare our work to a study performed for the same area by MARIN (Duursma et al., 2019) in Fig. 13.

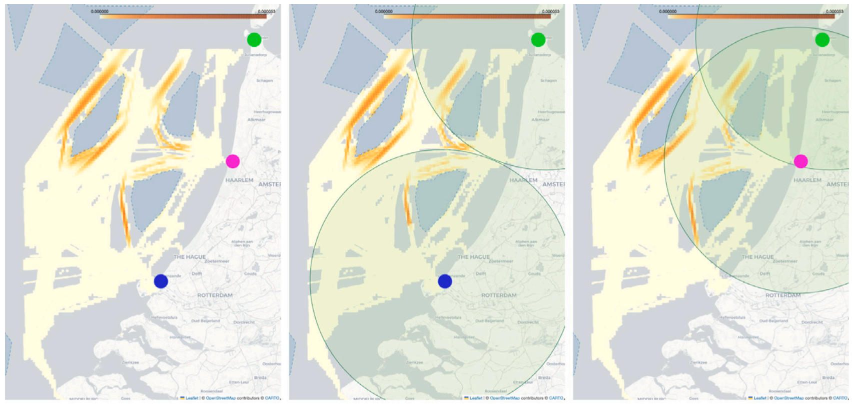
Two differences stand out. First, Duursma et al. (2019) evaluate the allision risks from the perspective of the wind turbines, indicating how frequent a particular wind turbine, or any turbine in a wind park, is contacted by a drifting vessel. Although this methodology allows for assessing various intervention measures, such as deploying emergency response vessels, the outcomes do not particularly assist to find the *right*, or even *best* measures, as it is unclear where the risks come from. In our approach, the risks are evaluated presented them from a nautical traffic perspective, whereby the outcomes can support identification of promising measures, as demonstrated in Fig. 12. Second, comparing Fig. 13(b) and Fig. 13(c), demonstrates the increase in resolution that we have achieved with our approach. This is required both for the outcomes, and in the entire analysis, to achieve the level of detail needed to understand local traffic influences, as was presented in Fig. 8. This comparison demonstrates the improved flexibility to valuate the risk-related outcomes from multiple perspectives and from various zoom levels.

5. Discussion

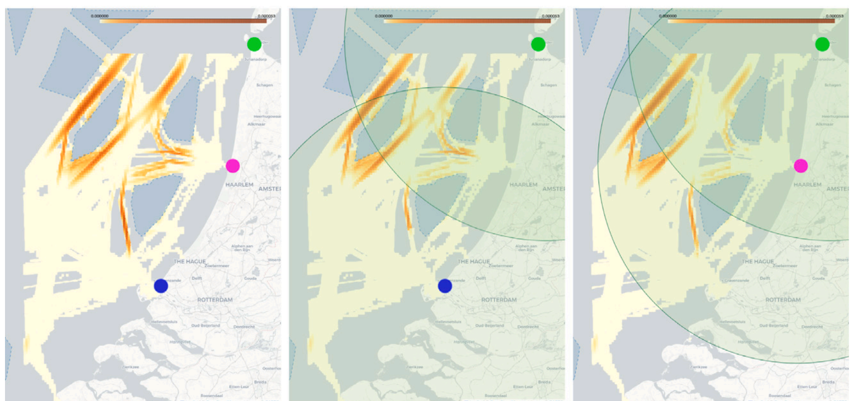
The approach presented in this article was demonstrated to provide extensive understanding of the probability on undesired events regarding NUC-vessels and their interaction with offshore infrastructure, in this case, wind parks. The most important competence of this approach is that it keeps track of background information, providing a basis for complementing the currently presented event table with better qualitative and quantitative probabilities that can be made conditional to the distinguished events (for example, vessel type or environment dependent). By carefully considering the definition of the events upfront, we assure that it is possible to distinguish between the relevant conditions, which is important when qualitative, possibly operational, input is gathered, for example about the deployment and limitations of ERTVs.

A particular and obvious aspect of risk analysis where this is of importance, is in defining consequences. So far, we have only considered the probability-side of the risks, however, it is feasible to complement the current scenarios with expressions of consequences. For example, smaller vessels may have small consequences when hitting a wind turbine, whereas large vessels may cause serious damage to the turbine and even the entire energy supply of the wind park. Furthermore, one can distinguish between cargo types, whereby tanker vessels cause a greater environmental damage than dry bulk vessels. Vessels carrying large numbers of passengers have different consequences, as rescuing hundred's of people from a cruise ship located in a wind park may be very challenging, if not, impossible. Formulating conditional consequence ratings or other quantification can further complement the understanding of allision risks, thereby emphasising the benefit of not just evaluating the "overall" risk, but connecting to the background knowledge, and extracting different perspectives.

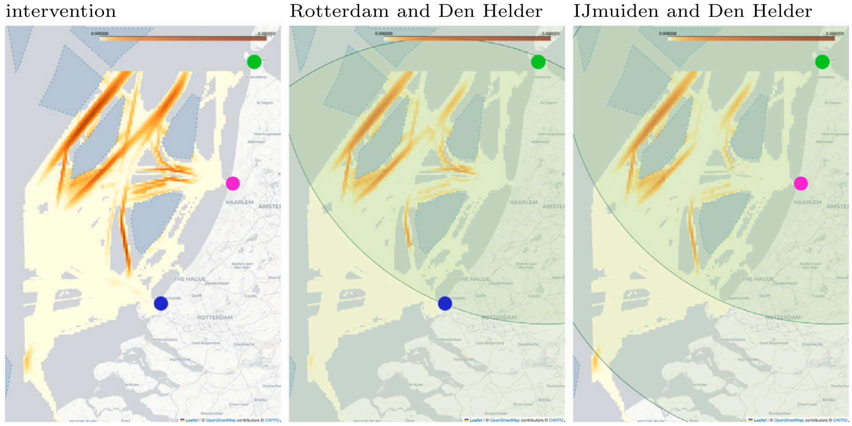
The same approach should be followed to improve currently incorporated scenario probabilities. For example, experts might be able to provide better estimates of the probability of getting adrift, under certain environmental conditions, or for specific vessel types. This concerns the deployment of the ERTV's, for example. Assessing the overall effectiveness of an ERTV is difficult, but operational experts might be able to indicate the likeliness that an ERTV is capable of



(a) Allision probability after 2 drifting hours, without ERTV intervention (b) Allision probability after 2 drifting hours, with ERTVs Rotterdam and Den Helder (c) Allision probability after 2 drifting hours, with ERTVs IJmuiden and Den Helder



(d) Allision probability after 3 drifting hours, without ERTV intervention (e) Allision probability after 3 drifting hours, with ERTVs Rotterdam and Den Helder (f) Allision probability after 3 drifting hours, with ERTVs IJmuiden and Den Helder



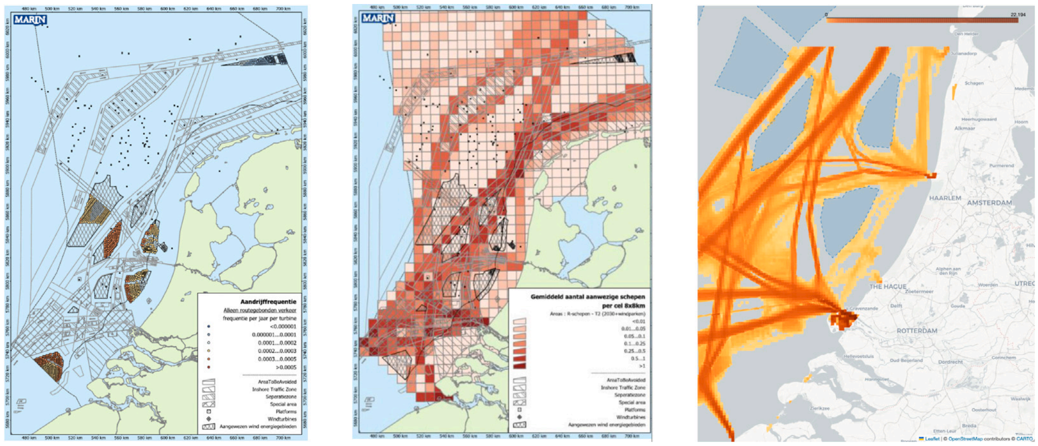
(g) Allision probability after 4 drifting hours, without ERTV intervention (h) Allision probability after 4 drifting hours, with ERTVs Rotterdam and Den Helder (i) Allision probability after 4 drifting hours, with ERTVs IJmuiden and Den Helder

Fig. 12. Allision probability after 2, 3, and 4 h of drifting (varying with rows), and without (first column) and with ERTV intervention stationed at Den Helder and Rotterdam (second column), and with ERTV intervention stationed at Den Helder and IJmuiden (third column). Den Helder marked green, IJmuiden marked pink, Rotterdam marked blue.

preventing a NUC-vessel from drifting a wind park under particular conditions and given a particular vessel type and size. Similarly, the response time of an ERTV can be defined as a function of the wave-, wind-, and current conditions. The presented approach may be used to assess the need for additional emergency vessels and can support in the investigation of the required capabilities, or specifications, for a potential new emergency vessel.

We also showed that keeping track of the background information provides a better understanding of the most important contributors to (high) allision probabilities. It gives the flexibility to extract particular weather conditions or vessel types, and to evaluate whether certain circumstances occur frequently, or whether the conditions result in a high probability of drifting into a wind park, or perhaps both. This knowledge can give direction in the process for the design of intervention measures, for example, supporting the balance between prevention (ensuring that some vessels do not appear in a certain area under specific condition) and response (increasing the number of ERTV's, or repositioning them).

In the presented analysis, hindcast input data was used to extract vessel densities as well as environmental conditions. The authors could imagine that there is a desire to incorporate potential future scenarios, reflecting climate change on the environmental side and fleet and



(a) Allision probabilities for individual wind parks as analysed by MARIN (Duursma et al., 2019)

(b) Vessel densities on grid as analysed by MARIN (Duursma et al., 2019)

(c) Vessel densities on grid as analysed with the approach presented in this paper

Fig. 13. Comparison between various types of outputs related to allision risk analyses.

vessel size increase on the vessel traffic side. The impact of future wind parks on the allision probability may furthermore be considered. This would require additional approaches and insights to estimate fleet composition and traffic densities, especially when shipping lanes are planned to be altered, however, the multi-perspective approach can still be applied to these scenarios.

Although we believe that the presented approach improves the transparency and the quality of allision risk assessments, uncertainties still remain. However, due to the large extent of flexibility, we also believe that the presented approach is suitable for addressing those uncertainties in the event table, aside from probabilities and consequences, as called for by Aven (2010). In similar ways as presented for the evaluation of probabilities, our approach can be used for identification of scenarios in which uncertainties may become significant, for example when combining future fleet scenarios with future environmental scenarios, potentially leading to the implementation of precautionary principles.

The most important uncertainties in the presented table, besides from the ones mentioned above, are related to the uncertainties in the drift model and the used input data. The use of 2019 AIS data puts limitations to the outcomes, as shipping routes were not yet adjusted in preparation to the planned offshore wind parks. The consequence is, that in the data, some traffic still regularly crosses through (future) wind parks, for example, the ferry departing from IJmuiden, that still crosses the wind park Hollandse Kust Noord (HKN). Furthermore, better supported expressions are required for the probability of getting adrift, since the applied probabilities throughout literature vary, as well as their bases (hourly, crossing-based, etc.). The event table provides flexibility to incorporate either type of expression, as well as values conditional to environmental conditions or vessel types.

We furthermore strongly recommend further research into the validity of the drift paths predicted by *OpenDrift* for a range of vessel types, as this was currently made for bulk carrier Julietta D. only. As was demonstrated in Section 3, the type and size of the vessel is an important driver of the likeliness that a vessel drifts into a wind park, and in particular, vessels with a large wind area, like cruise vessels and container vessels, are susceptible to these driving forces, whereby a small parameter change may cause significantly different behaviour. Comparative analyses between the *Opendrift* model and other models, for example time-domain models, as well as actual vessel drift paths from AIS-data can provide validation and identify improvement directions. Similar studies should investigate the influence of an initial vessel speed and direction at the moment of technical failure on the drift path of the vessel, as currently, this speed was assumed zero. Potential changes for the drift path outcomes may consequentially require reconsideration of the defined environmental bins.

6. Conclusion

Several reasons drove us to implement an event-based approach for the evaluation of allision risks on the North Sea. First of all, the aim was to improve the transparency of the analysis. This was accomplished by the establishment of the event table and keeping track of the background information for each event, allowing for thorough interpretation of the entire set of events. Consequently, a comprehensive approach from varying perspectives of the most important processes was derived by considering different table extractions at a time. The event-table concept furthermore provides a basis for uniting qualitative and quantitative assessments, whereby probabilities and consequences can be defined conditional to circumstantial conditions or vessel characteristics. The integrated effect of these assessments can subsequently be evaluated based on the event table using multiple perspectives. Designing of prevention or intervention measures can be supported in the same way. Finally, tying risks, or more specifically, probabilities and consequences, to distinguished events with associated background information, is a stepping stone to more explicit addressing of uncertainties.

Using the approach, we were able to derive a thorough understanding of allision risks in the evaluated area. By looking at spatial patterns, the role of the shipping intensity could be evaluated, emphasising the impact of (an increased) buffer zone. From a conditions perspective, it was found that the occurrence probability of environmental (wind) directions also has a significant impact. Combining these two aspects can support decisions for buffer zone sizes, given the orientation of the wind park with respect to the shipping lane, and taking into account these environmental conditions. The event table can be useful as slices can be extracted for particular areas, whereby the change in allision probability can be evaluated for a range of distances between traffic lanes and wind parks. Finally, the effectiveness of intervention measures can be assessed by evaluating different operational strategies for ERTV deployment, thereby also considering the limitations of its operational profile. The flexibility of deriving all these insights from a single data structure ensures the prerequisite to always trace back to underlying assumptions, and to obtain a clear understanding of mutual relations and performance.

Acronyms

AIS Automatic Identification System.

ECMWF European Centre for Medium-Range Weather Forecasts.

ERTV Emergency Response Towing Vessel.

EU European Union.

FSA Formal Safety Assessment.

GTSM Global Tide and Surge Model.

IMO International Maritime Organisation.

IWT Inland Waterway Transport.

NRA Navigation Risk Assessment.

NUC Not Under Command.

UK United Kingdom.

CRediT authorship contribution statement

Solange van der Werff: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Sietse Eppenga:** Writing – review & editing, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Arne van der Hout:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Pieter van Gelder:** Writing – review & editing, Supervision, Methodology. **Mark van Koningsveld:** Writing – review & editing, Supervision, Methodology.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Solange van der Werff reports financial support was provided by SmartPort. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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