Merging Multiple Perspectives to Extend Views on Nautical Systems

Case studies on safety monitoring, allision risks, and shipping emissions from a Scales, Conditions, Behaviour, and Dependencies perspective

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Solange Esmée van der Werff

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CASE STUDIES ON SAFETY MONITORING, ALLISION RISKS, AND SHIPPING EMISSIONS FROM A SCALES, CONDITIONS, BEHAVIOUR, AND DEPENDENCIES PERSPECTIVE

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Watching as the night turns to morning
The temporary tones of the sky
Remind me that we're always evolving
Nothing's ever black and white

Isa Azier & Son Mieux

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Summary

In the coming decades, the shipping sector is facing various challenges, requiring adaptations for achieving sustainable shipping, against climate change consequences, for facilitating alternative activities at sea, and for transitioning towards more autonomous shipping. Several incidents related to these challenges force us to take a good look at how the system can keep performing its function conditional to these changes. Scientific studies hereby regard the collective of (interacting) shipping activities as a system. Outcomes of data analyses and models are intended to support decision makers in designing effective improvement measures. However, the usefulness of the outcomes to the decision makers can be better, amongst others due to poor communication between science and decision makers, due to analysis objectives not being achieved, and due to unrealistic data requirements.

At the foundation of the analysis is often a disciplinary approach, or *way of thinking*, which determines which solution space is considered, and which input sources are accepted. Looking from multiple *perspectives* can broaden this, and thereby improve the formulation of analysis objectives and the identification of relevant input data. Besides determining which perspectives are relevant for a specific problem, the remaining challenge is related to how these alternative perspectives can be merged into an integrated whole. The aim of this thesis is to design a framework for an early integration of multiple perspectives in the analysis of shipping systems to improve their usefulness in the decision-making process. The first ambition for the framework is to provide a formulation of analysis objectives and data requirements in view of multiple perspectives, and the second ambition is to develop a data-structure concept to merge the perspectives.

For the first ambition, a literature study into systems with similar characteristics as a shipping system revealed that the analyses of these systems are mostly performed from one or several of the perspectives regarding its objectives, that we refer to as: (1) **scales**, addressing the "where" and "when" of system performance, uncovering spatial patterns and temporal variations, (2) **conditions**, considering the connection between system performance and its underlying physical processes and environment, (3) **behaviour**, considering the influence of individual or collective behaviour on the system performance and (4) **dependencies**, identifying causal relationships and sensitivities within the system. For each of the distinguished perspectives, based on the data sources and analysis types of the relevant studies, specifications could be formulated about the highest detail level on one hand, and the information required to aggregate to higher levels, up to the system level, on the other.

The second ambition, regarding a concept for merging these multi-perspective requirements, was obtained by introducing a new data structure referred to as an *event table*. In this data structure, inspired by the existing concepts of moving features and

event logs, each row represents a distinct event, and each column indicates a characteristic of the event. A single event is defined by the highest-detail-level specifications for each perspective. Besides some columns that form the unique event definition, the *attributes* provide additional information about each event. Filtering and aggregation operations on the event table allow zooming in and zooming out, offering flexibility to investigate global patterns in detail, or to assess the impact of detail level processes, thereby fulfilling the second ambition for the framework.

The framework outlines the relationship between the availability of input materials and the ambition of the analysis goals. Hence, developments in the field of data science, analysis techniques, and computational facilities increase the scope, detail level, and modeling complexity captured in the analysis goals. By parallelising and scaling-up computations, the scope and detail level of analyses can be increased. By joining multiple spatially and temporally varying data sources, environmental influences can be determined. By applying dimension-reduction and outlier detection techniques, many characteristics of vessel behaviour can be assessed to determine anomalous behaviour. By labelling known behaviour, cause and effect can be coupled to improve the predictive capabilities. Applying these developments to the monitoring activities regarding nautical safety demonstrated how these developments can extend the ambition level of the analysis.

The framework was applied to two shipping-related cases. The first case considered nautical safety risks at the North Sea imposed by the potential event that vessels get adrift while being surrounded by offshore infrastructure, like wind parks. Based on the formulated multi-perspective objectives, the event table was constructed, whereby each event was defined by combination of a vessel of particular type and size (indicated by a category), to be present at a particular location at sea (indicated by a cell, part of a grid), under particular environmental conditions (a combination of wind direction, wind speed, wave height-period combination, wave direction, and current profile). For each event, the probability of occurrence could be determined, and conditional to this, using a drift path prediction tool, the probability that the vessel would drift into a wind park after n hours in case of technical problems. Filtering and aggregation operations on the table revealed how a single analysis can support location specific design of barriers between wind parks and shipping lanes, as well as evaluation of strategies for emergency response vessels.

The second case considered shipping emissions on Dutch inland waterways. Based on the framework, analysis objectives were formulated for three perspectives; scales, conditions and behaviour. This resulted in an event table whereby each event corresponded with a single vessel, sailing a single waterway section on the Dutch fairway network. For each event, based on the sailed trajectory, the vessel properties, and the environmental characteristics, the energy use as well as the associated emissions could be estimated. The entire collection of events in the table represented all vessels travelling on the Dutch inland waterway network over the course of four months. Filtering and aggregation operations on the table revealed how emissions are impacted by river currents, and that a large share of the emissions is caused by waiting, idling, and manoeuvring vessels.

Both cases demonstrated how application of the framework can lead to an improved understanding of how the shipping system performs and responds to varying conditions and external changes. More importantly, they showed that the event table concept was capable of supporting formulation of promising improvement measures. This offers policy makers better support when making decisions. Owing to the versatility of the event-table concept, it is possible to anticipate on unseen or unforeseen perspectives in the future.

Samenvatting

De komende decennia staat de scheepvaartsector diverse uitdagingen te wachten, die aanpassingen eisen om duurzame scheepvaart te bereiken, om de consequenties van klimaatverandering te kunnen ondervangen, om in te spelen op het veranderende landschap op zee met de komst van nieuwe gebruikers, en om een overgang naar meer autonome schepen te faciliteren. Diverse incidenten gerelateerd aan deze uitdagingen dwingen ons om goed te bekijken hoe het scheepvaartsysteem goed kan blijven functioneren onder de veranderende omstandigheden. Vanuit een wetenschappelijk oogpunt wordt het collectief van (interacterende) activiteiten rondom scheepvaart gezien als een systeem. De uitkomsten van data- en modelanalyses zijn bedoeld om beleidsmakers goed te ondersteunen bij het ontwerpen van maatregelen. Echter, de bruikbaarheid van de wetenschappelijke resultaten is nog niet goed genoeg, onder andere door slechte communicatie tussen de wetenschap en beslissings- en beleidsmakers, het niet behalen van de gestelde doelen, en het stellen van onrealistische eisen aan de data.

Aan de basis van een analyse ligt vaak een domeinspecifieke aanpak, of *manier van denken*, die in grote mate de oplossingsrichting al bepaalt, en welke vormen van input geaccepteerd worden in de analyse. Daarmee is dit een beperkende factor. Door vanuit verschillende *perspectieven* te kijken, wordt het mogelijk om over deze beperkingen heen te kijken, en daarmee de analysedoelen beter te formuleren en relevante input data te identificeren. Naast het bepalen van de relevante perspectieven voor een bepaald probleem, is een belangrijke uitdaging het integreren van die perspectieven tot een geheel. Het doel van dit proefschrift is het ontwerpen van een raamwerk dat de integratie van meerdere perspectieven mogelijk maakt voor de analyse van scheepvaartsystemen, om zo de bruikbaarheid van de uitkomsten in het beslissingsproces te verbeteren. De eerste ambitie van het raamwerk is het formuleren van analysedoelen en data-eisen vanuit meerdere perspectieven, en de tweede ambitie is het ontwikkelen van een datastructuur waarin de concepten vanuit verschillende perspectieven gezamenlijk in kunnen worden ondergebracht.

Voor de eerste ambitie is een literatuurstudie gedaan op basis van systemen met vergelijkbare eigenschappen als een scheepvaartsysteem, die aantoonde dat analyse hiervan veelal gedaan wordt vanuit een of meerdere perspectieven gerelateerd aan het doel, die we omschrijven als: (1) **schalen**, dat gaat over het "waar" en "wanneer" van hoe het systeem functioneert, en de ruimtelijke en tijdsafhankelijke variaties blootlegt, (2) **condities**, dat de koppeling tussen (de prestaties van) het systeem en de onderliggende fysieke processen en omgeving behelst, (3) **gedrag**, dat gaat over de invloed van individueel of collectief gedrag op de prestaties van het system, en (4) **afhankelijkheden**, waarin causale verbanden en gevoeligheden in het systeem worden geïdentificeerd. Uitgaande van de databronnen en analyses horende bij de studies

voor elk van de onderscheiden perspectieven, konden specificaties worden geformuleerd over het hoogst benodigde detailniveau en de informatie die benodigd is om van die details naar een systeemniveau te aggregeren.

Om de tweede ambitie, een concept dat de eisen van meerdere perspectieven integreert, te bereiken, is een nieuwe datastructuur geïntroduceerd: een *event tabel*. Deze tabel is geïnspireerd op bestaande concepten van moving features en event logs. Elke rij in de tabel representeert een apart *event*, en elke kolom bevat informatie over het event. De definitie van een event is voor elk perspectief specificeerd op het hoogste detailniveau, en is vastgelegd in de eerste paar kolommen van de tabel. De andere kolommen bevatten *attributen*; aanvullende informatie over het event. Door te filteren en te aggregeren is het mogelijk om in- en uit- te zoomen, waardoor er flexibiliteit ontstaat om van globale patronen ook de details te bekijken, of om juist de globale impact van detailprocessen te onderzoeken. Daarmee vervult de event tabel de tweede ambitie van het raamwerk.

Het raamwerk benadrukt de relatie tussen de beschikbaarheid van databronnen en analysetechnieken enerzijds, en het ambitieniveau van de analysedoelen anderzijds. Ontwikkelingen op het gebied van datawetenschap, analysetechnieken en rekenfaciliteiten betekenen dus een verbetering van de scope, het detailniveau en de complexiteit die in de analysedoelen worden vastgelegd. Door paralleliseren en opshalen van berekeningen kunnen de scope en het detailniveau worden vergroot. Door het koppelen van meerdere bronnen met tijds- en plaatsafhankelijke data kan de invloed van omgevingsfactoren worden bepaald. Door dimensiereductie en detectie van uitschieters (outlier detection) kunnen vele karakteristieken van scheepsgedrag worden meegenomen bij het herkenenen van afwijkend gedrag. Door bekend gedrag te labellen kunnen oorzaak en gevolg aan elkaar gekoppeld worden om het voorspellend vermogen te verbeteren. Door deze ontwikkelingen toe te passen tijdens het monitoren van nautische veiligheid wordt duidelijk hoe zij het ambitieniveau van de analyse kunnen verhogen.

Het raamwerk is toegepast op twee scheepvaart casussen. De eerste casus omvat nautische veiligheidsrisico's op de Noordzee, veroorzaakt door de potentiële gebeurtenis dat een schip op drift raakt in het nabijzijn van infrastructuur in kustwateren, zoals windparken. Gebaseerd op de analysedoelen voor elk perspectief is er een event tabel geconstrueerd. Hierbij was elk event gedefinieerd door de combinatie van een bepaald schip (gecategoriseerd volgens scheepstype en -afmeting), dat op een bepaalde locatie aanwezig is (uitgedrukt als cel in een grid), onder bepaalde omgevingscondities (een combinatie van windrichting, windsnelheid, golfcondities, en stroming). Voor elk event is de kans op voorkomen bepaald, en vervolgens de bijbehorende kans dat een schip met technische problemen onder die omstandigheden binnen n uur een windpark in zou drijven. Hierbij is een tool gebruikt die het pad voorspelt van het drijvende schip. Filteren en aggregeren van de tabel onthulde hoe een enkele analyse iets kan zeggen over zowel strategische en ontwerpkeuzes (zoals de breedte van barrierezones om de parken heen), als over strategische en tactische keuzes over de aanschaf en inzet van noodsleephulpdiensten.

De tweede casus gaat over scheepsemissies op Nederlandse vaarwegen. Uitgaande van het raamwerk zijn analysedoelen geformuleerd voor drie perspectieven: schalen, condities en gedrag. Dit heeft geresulteerd in een event tabel waarbij elk event correspondeert met een uniek schip, dat één waterwegsectie aflegt binnen het netwerk. Op basis van het afgelegde traject, de eigenschappen van het schip, en de omgevingscondities, zijn voor elk event het energieverbruik en de bijbehorende emissies bepaald. De collectie van events in de tabel representeren alle schepen die gedurende vier maanden op de Nederlands binnenwateren voeren. Door over de tabel te filteren en aggregeren kon worden weergegeven hoe het ontstaan van emissies wordt beïnvloed door stroming op rivieren, en dat een groot deel van de emissies wordt veroorzaakt door schepen die wachten en manoevreren. Beide casussen demonstreren hoe de toepassing van het ontwikkelde raamwerk kan leiden tot verbeterd begrip over hoe het scheepvaartsysteem reageert op variërende omstandigheden en veranderingen van buitenaf. Bovendien is daarmee gedemonstreerd dat de event tabel in staat was om de concepten die bij meerdere perspectieven horen te integreren. Op deze manier kunnen uitspraken gedaan worden over de prestaties van het systeem, maar ook over de maatregelen die het best in staat zijn om het systeem te verbeteren. Dit geeft beleidsmakers betere ondersteuning bij het nemen van besluiten. Door de veelzijdigheid van dit concept is het mogelijk om te anticiperen op niet eerder geziene of voorziene perspectieven in de toekomst.

1

Introduction

Weten, weten, wil alles weten
Het is raar maar waar
Dat de wind hard waaien kan
Water bevriezen kan
Ik word er zo nieuwsgierig van
Het is raar maar waar

Jan Paul Schutten & Tjeerd P. Oosterhuis

1

1.1. Targeting safe and sustainable shipping

On January 31st, 2022, storm Corrie hit the Netherlands, with strong winds and heavy rains, causing damage to houses, infrastructure, and vehicles. However, the news that day was dominated by cargo vessel Jullietta D., which had been at anchor on the North Sea near IJmuiden. Although vessels commonly use this anchorage in severe weather conditions, in this case, a small failure had large consequences. During the storm, the anchor broke loose, sending the vessel adrift. Soon, it collided with a tanker at anchor, damaging the hull severely, but not enough to sink. Next, the Jullietta D. drifted into a wind park under construction, where it hit the foundation for a platform that was not installed yet. After about 9 hours of drifting, the vessel was connected to tugboats, that towed it to safer space at open sea, and into the Port of Rotterdam with daylight the next day.

In the Netherlands, 2022 was a year with much sunshine, and little precipitation. The discharge of the river Rhine was at an extreme low, with a minimum discharge of 679 m^3/s (van den Hoek and van der Mark, 2025). This drought had many consequences, among others directly for the natural environment, for the irrigation of farmland, but the low river discharges also had consequences for inland shipping. A reduced water depth for shipping (Agreed Low River discharge equals 1020 m^3/s, (Vinke et al., 2024)) forced ships to carry less cargo, requiring more ship movements and employment of other ship types (Vinke et al., 2022; Vinke et al., 2024). On top of that, the drought also decreased the navigable width of the river, thereby further increasing the shipping density on the river. At the river IJssel, takeovers were temporarily forbidden. To reduce the quantities of fresh river water flowing into the sea, several locks, like those in IJmuiden and Weurt, were only operated during restricted hours, and at a lower frequency, causing delays for ships. These happenings were not unique, since over the last years, extreme low river discharge rates have occurred multiple times. Moreover, the Intergovernmental Panel on Climate Change (IPCC) and the Royal Netherlands Meteorological Institute (KNMI) predict more frequent and more severe extreme river discharges as climate change progresses (Vinke et al., 2024; van den Hoek and van der Mark, 2025).

Together, these two stories illustrate important challenges that the nautical system is facing now, and even more so over the coming decades. On one hand, treaties like the European Green Deal (European Commission, 2019) pose ambitious goals to the shipping sector itself to become more sustainable and to increase its capacity. On the other hand, the shipping activities must adapt to changing conditions, ranging from severely varying water levels reducing the navigability at the rivers, to a spatial design at sea forcing more shipping activities into a smaller area, and in closer vicinity to energy-providing infrastructure. To reach targets while maintaining safety, it is important to understand what the consequences are of all these changes, whereby the difficulty is that local changes may have global impact, and global changes have varying effects at the local level (Heino et al., 2023). In the evaluation of these issues, the whole of the interacting shipping activities is regarded as a system, enabling the application of associated theories and approaches.

1.2. Characteristics of the nautical system

As a starting point for gaining an understanding of how a nautical system (in this dissertation sometimes also referred to as shipping system) performs, four characteristics are distinguished to represent it. The first characteristic is that it encompasses many different vessels, as becomes clear from Figure 1.1. This is a top-view snapshot of all vessels (with an Automatic Identification System (AIS)-beacon) present at the North Sea, at a particular moment in time. Vessel positions and headings at this instance are represented by triangles on a map. Depending on the goal of an analysis, a scale is chosen, for example, a port, a river, an entire sea or even the globe, and linked to that, a representation of these agents. For example, to understand terminal logistics within a port area, individual vessels are modelled as discrete *agents* (Bellsolà Olba et al., 2018; Durlik et al., 2023), tracking their individual actions (like taking multiple snapshots like Figure 1.1). On a different scale, weekly variations in vessel types are assessed on particular shipping routes to understand the consequences of drought on inland waterways (Vinke et al., 2022). Here, individual vessels cannot be distinguished any more, but it is still possible to exactly derive how many vessels of particular type crossed a particular fairway. On a global scale, vessels may just be represented lines connecting origins and destinations, with thicknesses indicating flows of vessel numbers or cargo volumes (Pratson, 2023). Hence, the evaluated scale drives the detail levels to represent the system with (Siegenfeld and Bar-Yam, 2020).

As a second characteristic, how the nautical system functions, is influenced by the interaction between the vessels and their environment. Obviously, in terms of safety, stormy conditions with strong winds and high waves increase the probability of incidents compared to calm weather, due to technical problems, poor visibility, and vessel crew that may be impacted by severe vessel motions. But even in more day-to-day conditions, the environment has a big impact. Sailing against the current drastically increases a vessel's energy use (Eger et al., 2023), and the same goes for head wind. A limited water depth also increases its resistance (Zeng et al., 2019; van Koningsveld et al., 2023; M. Jiang et al., 2023), and may even restrict unobstructed sailing into port areas (due to tidal ranges, see F. P. Bakker et al. (2024)), or further inland (due to river discharge levels, see Vinke et al. (2022)). Not only do these conditions vary in space and time, they are encountered by vessels that themselves are moving through space and time. Understanding which solution works, requires understanding how performance of the nautical system depends on the encountered operating conditions.

The third characteristic is the fact that each vessel has their own decision maker on board, who through a sequence of actions (adjusting engine power, or rudder angle, etc.) ensures the vessel safely reaches destination, while responding to and anticipating on the encountered conditions and potential other traffic. Furthermore, different vessel types behave differently. For example, very large vessels stay in the deepest shipping channels (refer to the vertical lines in the left of Figure 1.2 indicated by nr. 1), routes of ferries can be distinguished based on their destination (refer to the trajectories departing from IJmuiden in Northwesterly direction in Figure 1.2 indicated by nr. 2), and construction vessels continuously sail back and forth between the port and wind parks (refer to the sharp, bright, points in a grid pattern in Figure 1.2 indicated by nr. 3, being individual wind turbines). Anchoring patterns (cloud-shaped

Figure 1.1: Screenshot of instantaneous vessel traffic in the Netherlands and at the North Sea (*MarineTraffic.com*), with circles indicating anchoring or moored vessels, and triangles indicating sailing vessels. Different colour shades indicate various vessel types (tankers, container vessels, fishing vessels, etc.), and marker sizes indicate vessel sizes.

forms all the way in the West and just (South)east of the main shipping lanes in Figure 1.2 indicated by nr. 4) can be discovered by evaluating tracks over time, as well as fishing and dredging patterns (refer to the dredging activities at the coast in the North of Figure 1.2 indicated by nr. 5). Although it is possible to see these patterns, having a slightly different view can significantly improve identifying them. In Figure 1.3, a colour scheme is applied to indicate a vessel's speed. This emphasises the difference between route-bounded vessels (sailing at high speed, indicated with yellow), and anchoring or dredging vessels (sailing, or drifting, slowly, indicated with blue).

Figure 1.1 shows the distribution of vessels in space at a certain instance, and although it gives an indication of the shipping density, understanding how much distance vessels keep between each other requires zooming in, and probably evaluating multiple moments in time. Furthermore, to extract the high-level shipping patterns would require an entire time span of observations. Such a representation is on the other hand offered by the heatmap in Figure 1.2. Reversely, this figure provides the main shipping patterns, but it does not provide an understanding regarding distance-keeping, like a zoom-in of Figure 1.1 would, or on the individual behaviour of vessels, for example their speeds. Combining the insights we get from looking at all three figures already provides a lot more understanding. However, even jointly, these figures are not comprehensive, since, for example, the role of environmental conditions cannot be taken into account. To do that, we would require another *perspective* on the system.

The fourth characteristic is the high level of interdependencies between all actors. Consequently, changes in the system may initiate cascading effects, making the overall response to those changes, as well as to measures, nonlinear and unpredictable. An extreme example of this is the Suez-canal blockage of 2021, where an action of a single vessel caused a major disturbance in the global nautical system. Container vessel *Ever Given* stranded and blocked the entire cross section of the canal for six days, causing a queue of about 450 vessels waiting to transit (Russon, 2021). Furthermore, vessels that were rerouted needed about 8 days and 3,500 nautical miles more to travel from Asia to Europe. Aside from this extreme event, mutual dependencies between subsystems or individual vessels are of day-to-day importance when considering port calls and availability of terminals and quays (F. P. Bakker et al., 2024; F. P. Bakker, 2025), whereby large vessels are subject to tidal accessibility restraints, and smaller vessels have to subsequently wait their turn to enter. Even more directly, these connections are found around locks, where vessels may have to wait for other vessels before they can transit through.

The collection of these four characteristics is not necessarily a comprehensive nautical system description, nor are these characteristics strictly independent. For example, interdependencies between vessels strongly depend on the behaviour of vessels. However, for the further reasoning in this thesis, the presented four suffice. Furthermore, these characteristics are not exclusive for a nautical system. For example, the road traffic system has a similar nature, with vehicles moving on the road network, thereby mutually influencing each other and being affected by the circumstances (rain, snow, road works, etc.), causing drivers to delay their departure, take detours, or even not to travel (by car) in case of disturbances. Even systems that are

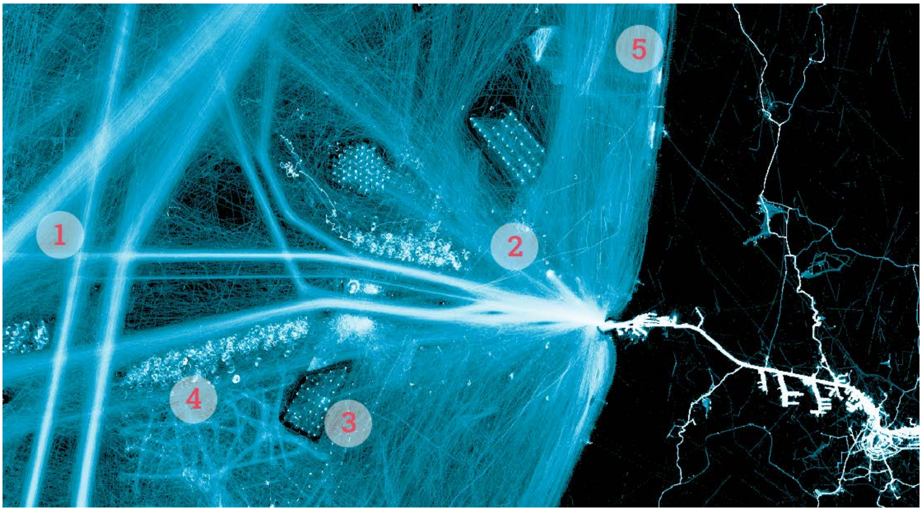


Figure 1.2: High-detail heatmap visualisation of vessel positions during four months, showing Amsterdam in the East, IJmuiden in the middle and the North Sea in the West. A brighter colour indicates higher traffic intensity. Numbers indicate (1) main shipping lanes, (2) ferry tracks, (3) offshore wind park, (4) anchoring area, (5) dredging activity.

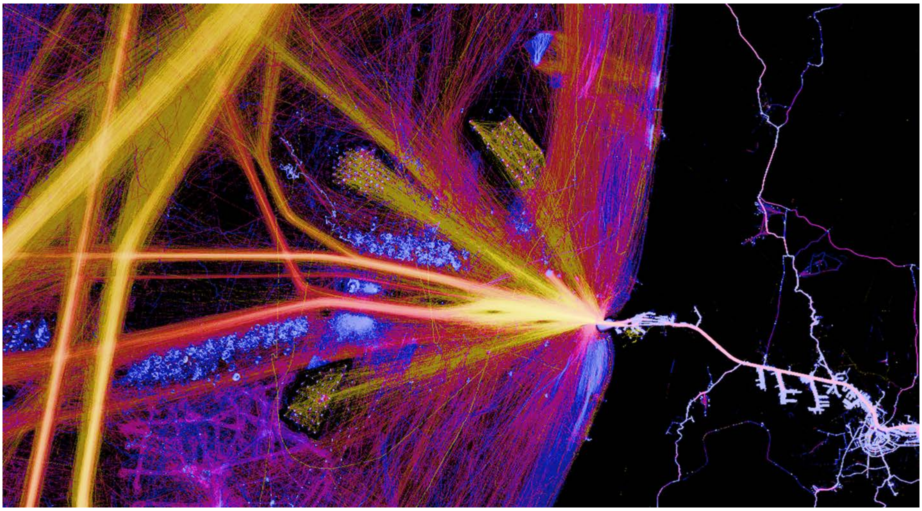


Figure 1.3: High-detail heatmap visualisation of vessel positions during four months, showing Amsterdam in the East, IJmuiden in the middle and the North Sea in the West. Colours indicate sailing speed, with blue the slowest, and yellow the fastest.

Figure 1.4: Container vessel *Ever Given* blocking the Suez canal for six days during 2021, causing a global nautical-system disturbance. Photo: Roscosmos/Handout via Reuters

apparently very different, have similar characteristics, like particular systems in the human body. For example, in the blood system, transporting cells, whereby its performance is affected by the direct environment, but perhaps also by external factors like medicine. The aim of this thesis is not to find a solution or approach that fits every single one of these examples, but it is important to realise the resemblances, as existing approaches for these systems may already exist.

1.3. Understanding a system requires multiple perspectives

"We must know the system in order to strengthen it," (de Savigny et al., 2009). When it comes to designing improvement measures, we require a good understanding of how the systems work. The *we* in this sentence is important when considering how to obtain this understanding. *We* as scientists use outcomes of models we developed and data analyses we performed. However, *we* (or *they*), being the decision makers, have difficulties to actually use these outcomes as a basis for or in support of the decision-making process. Coussement and Benoit (2021) stress that while many advancements have been made to the data analysis techniques, the interpretability and usefulness of the outcomes to the users have been neglected.

Although this is often linked to the complexity of modern analysis techniques, such as Machine Learning (ML), that are experienced as "black boxes" (Gosiewska et al., 2021), this issue was already addressed decades ago: "The proponents of mathematical modelling and computer technology generally have done a very poor job of translating outputs into terms that are readily understandable to those not so intimately involved in the art," (Biswas, 1975). As most important reasons, Biswas (1975) mentions poor communication, the extensive and sometimes even unrealistic data requirements, the incapability of models to meet the objectives, and models tending to be inflexible.

For decision makers to rely on the outcomes of (complex) scientific models and analyses, these outcomes need to be made comprehensible, transparent and credible to them (Kolkman et al., 2005; Siew, 2008; Coussement and Benoit, 2021). Looking from multiple perspectives can improve the decision-making process. Aiming to better connect science and decision-making, Siew (2008) introduced a framework based on a technological, organisational and personal perspective, as promoted by I. Mitroff and Linstone (1993) in their concept of Unbounded Systems Thinking (UST). More generally, Crilly (2024) observed how many institutions, ranging from commercial to governmental, and from local to international, adapted new *ways of thinking* "to encourage new perspectives, expand imagination and boost creativity."

These ways of thinking (design thinking, systems thinking, entrepreneurial thinking, scientific thinking, etc.) are connected to distinct disciplines and how they identify, describe, and solve problems. "The worldview of each perspective determines the "lens" through which a problem scenario is viewed and on which action is taken," (Hall et al., 2005). For example, P. Jackson (2006) describes geographical thinking as "a unique way of seeing the world, of understanding complex problems and thinking about inter-connections at a variety of scales (from the global to the local)", and Senge (1997) describes systems thinking as "a discipline for seeing wholes, as a framework for seeing interrelationships rather than things, for seeing patterns of change rather than static".

Hall et al. (2005) states that the used "lens" influences the solution space, or goal, as well as the mode of inquiry: "Each perspective limits the amount of information deemed relevant in any situation by further segregating information according to other dimensions [...]" From the expressions for geographical and systems thinking, it can indeed be derived that information is used differently to represent reality. Where P. Jackson uses (geographic) inter-connections, Senge uses dynamic high-level patterns. Other disciplinary approaches have similar concepts, for example, Noll (1935) describes scientific thinking using "habits", Sarasvathy (2008) describes entrepreneurial thinking using (behavioural) "principles", and van der Aalst et al. (2007) describe process mining using "events".

1.4. Research gap

Studies (in general, but those related to the challenges related to nautical systems are no exception) are usually conducted based on a specific disciplinary approach (Crilly, 2024). The associated "lens" determines the way the world is seen, driving both the considered solution space (the analysis objectives) and the accepted input sources. Biswas (1975) highlights exactly these two issues - not meeting analysis objectives and unrealistic data requirements - as reasons why the incorporation of scientific output in the decision-making processes falls short.

The question rises whether using multiple lenses - multiple perspectives - can contribute to solving these issues. In general, considering alternative perspectives (*divergent thinking*) creates a more complete image of the problem (Singer Jr, 1959; I. Mitroff and Linstone, 1993), and facilitates a broader range of considered solutions and increased openness to alternative input sources (Hall et al., 2005). Hence, incorporating multiple lenses contributes to the transparency of the approach and the comprehensiveness of the solution.

A remaining challenge is, once multiple perspectives on a matter have been developed, how to merge them, to come to a concrete decision (Singer Jr, 1959; I. Mitroff and Linstone, 1993; Hall et al., 2005). Thus far, no approaches have been developed to express different system perspectives so that they can be concretely joined into a single data structure. Hence, a concept is lacking that facilitates evaluation of a system from multiple perspectives. In this thesis, the quest is to find the relevant perspectives, e.g., "lenses" to look through, and to create a suitable way to merge them into an integrated view on the nautical system, that serves well-informed decision-making regarding the current and upcoming challenges.

1.5. Aim of this thesis

The aim of this dissertation is to design a framework for an early integration of multiple perspectives in the analysis of nautical systems, to improve their usefulness in the decision-making process around shipping-related challenges. Such a framework should address the formulation of multi-perspective objectives and associated requirements for input sources, and furthermore, it should provide a suitable concept to merge these perspectives. First, the foundation and development of a framework that can achieve these objectives, are considered. Hereby, the following research questions are to be answered:

1. *Which perspectives on nautical-system analysis objectives should be considered to derive corresponding requirements for the data and tools?*
2. *What concept can facilitate merging multiple analysis perspectives into an integrated whole?*

The fact that the framework incorporates multiple perspectives, may demand changes to currently applied approaches to achieve analysis results. It is important that the application of the framework will not be at the expense of the ability to make use of modern data-science techniques, among which ML. On the contrary, the framework should support using state-of-the-art analysis techniques, based on real-world applications. Therefore, the following research question will be addressed:

3. *How can data-science techniques broaden the applicability of the perspectives in the framework for nautical safety monitoring at the Dutch North Sea?*

Finally, this dissertation describes how well the framework can be applied to concrete nautical challenges, and to what extent the outcomes provide a better foundation for decision making. It is furthermore evaluated in view of advanced analysis techniques for visualisation and ML. This is reflected by the following research questions:

4. *How can generating an event table through the multi-perspective framework improve the assessment of allision risk-mitigating measures at the Dutch North Sea?*
5. *How can generating an event table through the multi-perspective framework improve the design of effective emission-reduction measures for the Dutch inland nautical system?*

1.6. Outline

The outline of this thesis is graphically shown in Figure 1.5, consisting of four layers. The framework design forms the foundation (bottom layer), and together with the applicability of state-of-the-art analysis techniques, it forms the basis for the third layer, being two real-world nautical cases in which the framework is implemented. Finally, conclusions are formulated about the approach based on the case outcomes (top layer).

More specifically, Chapter 2 introduces the design of the framework in view of challenges posed by the analysis and decision-making processes for systems with the characteristics described in Section 1.2. By evaluating a range of systems, several perspectives can be distinguished and defined, thereby addressing the first research question. Furthermore, a coupling is made between the analysis objectives and the requirements for the input data and data concept, in response to research question 2.

In Chapter 3, specific data-science challenges are identified in the context of a nautical-traffic monitoring case for Dutch North Sea coastal waters. Important steps in the process are to unite multiple data sources on a spatial-temporal basis, and to use ML-techniques to identify behaviour that deviates from normal. Jointly, these techniques contribute to more efficient and better targeted detection of anomalous vessel behaviour.

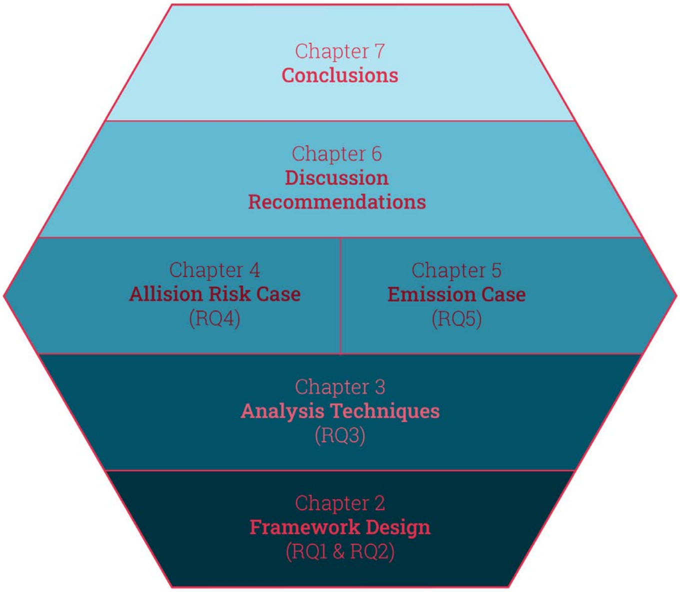


Figure 1.5: Outline of the dissertation

Chapters 4 and 5 describe the application of the framework to cases related to nautical safety and shipping sustainability. Chapter 4 considers safety on the Dutch part of the North Sea (research question 4). Here, using the framework, scenarios are defined that provide the basis for a risk assessment on collisions between drifting vessels and coastal infrastructure. This requires unifying AIS data, environmental data, spatial design features, and a drift path prediction tool, into integrated perspectives on the probabilities and conditional probabilities of these undesired events.

In Chapter 5, the framework is applied to the case of shipping emissions for the Dutch inland nautical system (research question 5). In this application, data sources on vessel tracks as well as fairway characteristics, are combined with an engineering approach to estimate the energy use of vessels. The framework is used to translate these outcomes into a better understanding of the main contributing factors of inland shipping emissions. This is inevitable when designing feasible measures to gradually reduce the emissions.

2

How Early Integration of Multiple Analysis Perspectives can Enhance System Understanding

Third eye view
Reveals the route

Tim Eijmaal, Sven Figee, Glenn Gaddum, Joost Kroon, Ivan Peroti

Due to their complexity, many agent-based systems are evaluated from isolated domain-specific perspectives, making it difficult to couple their outcomes. How can we support making our model results available for interpretation in other fields, without knowing what kind of information these fields require? Inspired by systemic approaches, we look from various perspectives. By reviewing studies evaluating these systems, the following chapter addresses research question 1: ***Which perspectives on nautical-system analysis objectives should be considered to derive corresponding requirements for the data and tools?*** Furthermore, this chapter considers the required associated data structure, as formulated in research question 2: ***What concept can facilitate merging multiple analysis perspectives into an integrated whole?*** The derived data structure enables directly complementing outcomes based on one perspective with those of other perspectives, improving integrated views on the system. Due to this flexibility, the framework helps to better prepare results for reuse by other unknown domains.

This chapter has been submitted as **S. van der Werff, P. van Gelder, F. Baart, and M. van Koningsveld**, *Overarching Domain Perspectives for Agent-Based Systems*, Under review with Data & Knowledge Engineering (2025)

2.1. System analysis perspectives

Consider activities related to the planning and layout of a port. Generally, this requires a geospatial view, resulting in analyses having a predominant Geographic Information System (GIS) perspective. Port development plans can be visualised directly at different points in time, and highlight space utilisation and potential conflicts during development phases. However, how do we decide, based on this viewpoint, for which stakeholders we should and should not provide access to port facilities? How can these analyses help shaping the long term goals related to this? In many cases, the solution would be to change standpoint and re-analyse from a business-domain side. Because of their different conceptual basis, the disadvantage is that the two viewpoints are difficult to unite. To address issues like these, we seek a means to exchange model outcomes and data between different domains and disciplines.

The two viewpoints in the above example can be seen as looking at the problem through two different "lenses" (Hall et al., 2005). The lens affects the solution space, or goal, and influences the mode of inquiry, driving the selection of relevant information, and the dimensions according to which this information is segregated. Various disciplinary approaches, or *ways of thinking*, as outlined by Crilly (2024), can also be regarded as different "lenses", and correspondingly, each of them identifies, frames, and solves problems differently. For example, Senge (1997) frames systems thinking as "seeing patterns of change rather than static", and P. Jackson (2006) describes geographical thinking to focus on "inter-connections at a variety of scales". The various lenses use different concepts to describe reality. For example, Noll (1935) describes scientific thinking using "habits", Sarasvathy (2008) describes entrepreneurial thinking using (behavioural) "principles", geospatial disciplines use the concept of features (Consortium, 2019; Asahara et al., 2015; Mokbel et al., 2024), and van der Aalst et al. (2007) describe process mining using "events".

For evaluating systems in particular, the worldview used to analyse it, matters as well. The systems-theory complementary law states that "[a]ny two different perspectives (or models) about a system will reveal truths regarding that system that are neither entirely independent nor entirely compatible" (Weinberg, 1975; Skyttner, 2001). The worldview is influenced by the disciplinary background of the scientist. Bunge (1979) distinguishes between the approach of a systems "specialist", who focuses on the structure and behaviour of systems, as opposed to that of the "standard scientist, engineer or social scientist", who focuses on physical relations between components, thereby applying a particular science.

What is considered to be a system, depends on the analyst's worldview, and how they represent it. This is reflected by the definitions and descriptions of a system, being for example "a way of looking at the world" (Weinberg, 1975), "what is distinguished as a system by the investigator" (Klir, 1985), "parts in relation" (von Bertalanffy, 1968), or "a set of interrelated elements" (Ackoff, 1971). The differences in formulated definitions by different scientists arise from the (levels of) specialisation or generalisation, their subset, their language use, their perspective, and their field of application (Dori and Sillitto, 2017).

The increasing complexity of the real-world (Lukyanenko et al., 2022) calls for solutions that go beyond separated worldviews. Referring back to the dilemma in the first paragraph, we want to ensure that essential insights regarding stakeholders are not overlooked when only using the GIS perspective to determine the port planning. In his work, Crilly (2024) looks beyond separated disciplinary approaches to establish their commonalities and their distinctions, to increase awareness of how other ways of thinking can complement any given disciplinary approach. The next question is, how can we accomplish an integrated view without knowing exactly upfront which information is required from the different perspectives?

The goal in this chapter is to formulate multiple perspectives that jointly provide an integral view on a system, and a data structure that facilitates integrating these perspectives, so that it can be used by scientists from varying domains and disciplines. Such a framework provides clearer support for the selection of data and information, as well as the formulation of analysis concepts, in a disciplinary-overarching way. We focus on a subset of real, concrete, hybrid systems (Ackoff, 1971; Bunge, 1979; Dori and Sillitto, 2017), with characteristics of a so-called complex system (Flood and M. C. Jackson, 1991).

To demonstrate the application of the framework, we consider three cases in the nautical field. These systems are characterised by their consistence of many interacting physical agents, being individuals or objects producing a particular effect by its action (Cambridge Academic Content Dictionary, 2024)), who's description strongly depends on the evaluated scale (Siegenfeld and Bar-Yam, 2020). Environmental and circumstantial conditions influence their behaviour, as well as that of integrated systems or system parts (Bar-Yam, 2002). Another characteristic is that interdependencies between system components result in unpredicable cascading effects (Bar-Yam, 2006; Randall, 2011). The application cases show how the framework is used to select data sources and to come to a data structure that can be used for a multi-perspective analysis.

2.2. Conceptual model framework

Conceptual models play a pivotal role to translate reality into a representation of reality, that is constrained by the scientist's definition of the system, and consists of constructs (Akoka et al., 2024), or concepts, being "structured collection[s] of knowledge describing a phenomenon from the Universe of Discourse" (Battista et al., 1989). In their representation of a scientific process, I. I. Mitroff et al. (1974) describe the Conceptual Model as one of four elements, refer to Figure 2.1, and specify the conceptual model as "the field variables that will be used to define the nature of the problem and the level to which the variables will be treated, for example, whether from a micro or macro point of view". Hence, our framework focuses on the design of the conceptual model. According to Guarino et al. (2019), the conceptual model describes how "we" conceive a specific domain, e.g., how the system is defined and represented, depends on the observer.

Although efforts are made to connect various disciplines, Skyttner (2001) observes that cross-scientific research does not succeed "so long as the involved disciplines depend upon their own methods and language". Furthermore, Lukyanenko et al. (2022) recognise the differences between different (stakeholders') conceptual models, and identify the need to "reconcile these differences into a unified conceptual model which

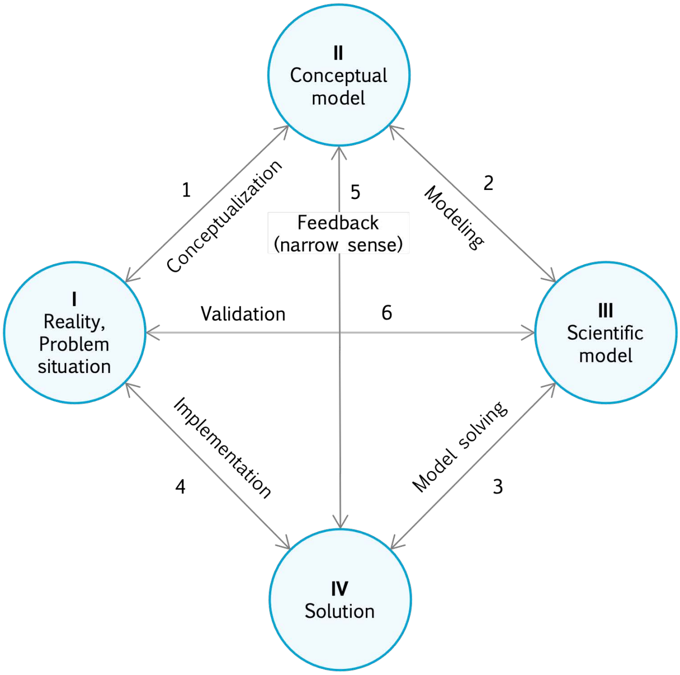


Figure 2.1: Four phases of scientific activities by I. I. Mitroff et al.

is effective and acceptable by the stakeholders for facilitating development and use of technology".

Systems specialists use multiple perspectives that jointly describe the structure and behaviour of a single system. For example, in the CESM model (Bunge, 1979), a concrete system is represented by its Composition, Environment, Structure and Mechanism, and in the CATWOE model (Smyth and Checkland, 1976), a system's root definition consists of the six elements Customer, Actors, Transformation process, Weltanschauung, Ownership and Environmental constraints. Lukyanenko et al. (2022) proposed CESM(+) as a design template for representing systems in a conceptual model, and underline the remaining challenges in representing the different perspectives, specifically the environment and the structure that captures the dependencies among the components.

The representation of the different perspectives, and how to obtain an integrated data concept, is the purpose of our framework, and its added value is explained in Figure 2.2, following the four phases defined by I. I. Mitroff et al. The conceptual models A and B are based on concepts from distinct disciplinary approaches. Consequently, they result in different scientific models, addressing different aspects of the system in their visualised outcomes. Because their underlying concepts are different, connecting these outcomes is very difficult. In contrast, conceptual model C incorporates concepts from multiple disciplinary approaches, resulting in a single scientific model. Consequently, the same outcome aspects can be generated as for A and B separately, however, there is an inherent connection between them, through the underlying physical processes captured in a single data structure.

To arrive at the foreseen framework, the following steps are undertaken:

1. Define physics-oriented system perspectives
2. Derive requirements for the selection of data sources and disciplinary concepts
3. Formulate the framework based on these requirements

In the first step, physics-oriented system analyses are reviewed to distinguish associated system perspectives. Thereby, a connection is made between the analysis objectives, and the corresponding approaches. The second step entails deriving the requirements to fulfill the objectives that are tied to various objectives. In the third step, we use the perspectives and corresponding requirements as a basis for deriving the anticipated framework. The three steps are described in sections 2.2.1, 2.2.2 and 2.2.3, respectively.

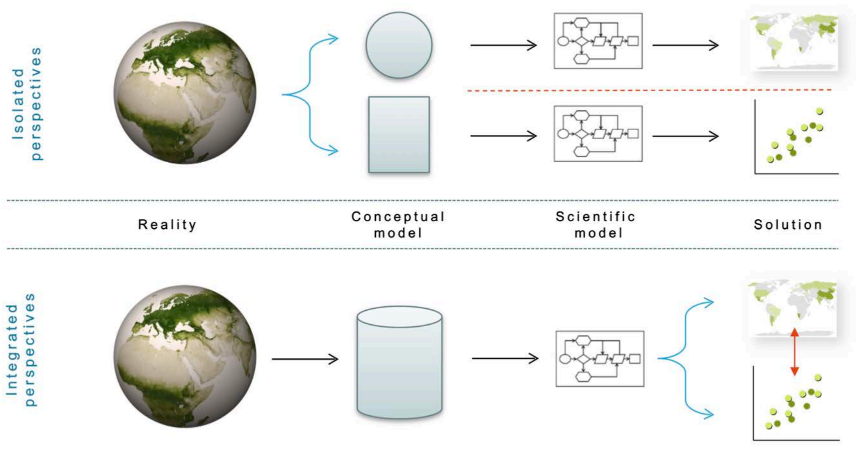


Figure 2.2: Visualisation of the difference between using isolated perspectives (top), whereby two separate conceptual models result in unconnected perspectives on the solution, and integrated perspectives (bottom), whereby one integrated conceptual model results in connected perspectives on the solution.

2.2.1. Definitions of perspectives

A system analysis, including methods and analysis techniques used, is the result of a balancing act between the research objectives and the availability of input knowledge and data sources. The basis for our framework is to understand their relationship. We do this by considering various physics-oriented, disciplinary approaches to represent and evaluate (complex) agent-based systems. Examples are road traffic, whereby the behaviour of individual cars creates patterns on the road network, and migration, whereby the agents in the system can be humans, insects, or other kinds of animals.

Related to that, how viruses spread and diseases in general and mutate, is also considered to be a (complex) system, and so is the human body itself, as well as most of its subsystems.

Based on various studies considering system analysis, we distinguished four perspectives that characterise the way the system is represented:

Scales The *scales* perspective is regarded in most analyses, considering spatial patterns and temporal variations. Examples are the spread of viruses over time and in space, determining where infection hotspots occur (Bag et al., 2020; Islam et al., 2021; Kianfar and Mesgari, 2022), and zooming in on the detailed processes, to evaluate the origin of local outbreaks (Barrios et al., 2021). In more and more studies, specific attention is addressed to enabling an evaluation at an arbitrary scale and to couple processes at micro- and macroscopic scales, for example in the evaluation of traffic systems (Yang et al., 2021) or on how a disease affects different levels and subsystems in the human body (Wolkenhauer et al., 2014; Borau et al., 2023). From this perspective, the system characteristic emergence can be considered as well.

Conditions The *conditions* perspective seeks to understand how system performance is influenced by its environment by considering the physical aspects that affect agents. Variations of the environmental conditions in space and time make it difficult to directly relate how processes are influenced by the circumstances they are situated in. This perspective tries to establish the effect of these conditions, hence, with the prerequisite that the scale perspective is considered as well. As an example, medical-focused studies aim at uncovering how conditions related to a person's unique personal health, DNA, or habits affect treatments. To improve personalised treatment, Algavi and Borenstein (2023) investigated the chemical properties of a range of drugs conditional to the genomic content of gut microbes. Based on a patient database, Diva et al. (2008) established how gender, age, or residence affect the hazard rates for multiple forms of cancer.

Behaviour The *behaviour* of individual agents influences how the system as a whole performs. It requires understanding the sequence of actions performed by these agents, like depicted in a Gantt chart (Wilson, 2003). As these actions are a consequence of the decisions that they make, in case of agents being humans, this would regard "human factors". Various studies have been conducted to analyse the change in travel behaviour as a result of various restrictions or lockdowns during a pandemic, for example, indicating shifts in the transport modes and the origins and destinations of the undertaken journeys (S. Li et al., 2022; Tao et al., 2023). Research into migration uses this perspective to understand how large-scale migration patterns arise from choices of individuals. Sorel et al. (2024) studied how the interaction with the environment drives the behaviour of locust swarms, resulting in a better understanding of their migration routes. Nourali et al. (2024) investigated how repeated coastal flooding events influence individual human migration decisions, and projected this to long-term changes in local-scale migration patterns. They concluded that the "factors that drive people to move at local scales may be quite different than at large scales and include factors such as housing, family, and educational opportunities." (Nourali et al., 2024) Hence, both examples illustrate that in order to evaluate a system from the behaviour perspective, it is inevitable to incorporate the scales and conditions perspective as well.

Dependencies The *dependencies* perspective focuses on identifying causal relationships, critical paths, and sensitivities within the entire system. It considers how actions of an agent or agents influence actions of others, for example, identifying the most important triggers that cause injury in road accidents (Topuz and Delen, 2021), or understanding the response of traffic flows to events like congestion or accidents (Queen and Albers, 2009). Furthermore, this perspective is often used to investigate the sequence of events leading to accidents (D. L. Cooke, 2003; Düzgün and Leveson, 2018; C.-H. Li et al., 2021). To determine these interdependencies requires considering how performance changes through time and space. It is also necessary to understand what the external conditions are, as well as how agents or processes behave, in general, and specifically in response to some initiating event. Hence, it is impossible to evaluate a system from the dependencies perspective without considering the scales, conditions and behaviour perspectives as well.

The perspectives in the presented order build on to each other; they are progressively complex. Furthermore, not every perspective is relevant for each considered case, and on the other hand, not every perspective can always be analyzed based on the available data and models.

The distinguished perspectives have similarities with the CESM model (Bunge, 1979) and the CESM+ model (Lukyanenko et al., 2022). The conditions perspective can be linked to the environment element in the CESM(+) model. However, where Lukyanenko et al. (2022) indicated the challenge to connect system behaviour and structure to its environment, we use directly link spatial and temporal variations of the environment to the movements of (physical) agents. The behaviour perspective resembles the structure in the CESM(+) model, whereby both focus on the processes within the system. However, where Bunge considered the description of components as a separate element (composition), the behaviour perspective in our framework also entails the identification of individual agents or collectives, as this determines the physical processes that can be evaluated. The scales perspective is not considered as such in the CESM(+) models, which is in our framework an important tool for zooming in and out, when considering temporal and spatial patterns. Finally, Bunge considers Mechanisms to be the element that distinguishes a concrete system from a conceptual system (described by the CES model), entailing particular (sub)processes of the system, which is quite different from our dependencies perspective, strictly focusing on interdependencies between actions of individual agents or collections thereof.

2.2.2. Analysis requirements related to the perspectives

Due to the progressive complexity of the four perspectives, the requirements of the materials must be considered cumulative. Based on the potential analysis aims, we can specify the requirements for the data sources. Furthermore, the data-science techniques related to the perspectives, as reviewed in the previous section serve as inspiration.

Scales To provide patterns in space, data should have space-dependent components, indicated with geometry attributes. Likewise, to provide patterns over time: data should have time-dependent components, indicated with timestamp (a point in time), time period (start and end time), range (start, end time and frequency) or time series (multiple timestamps) attributes. Multi-level outcomes require (adding) a “zoomable” component to the data. Hence, lowest-level data components must allow for aggregation. For example, if each data sample has a timestamp containing date and time, it is possible to aggregate by hour, week, month or year. Aggregation in space requires a spatial hierarchic structure, which can be formed by natural or political borders (municipality, province, or country). Furthermore, such a structure can be application-specific, such as the road network, or the anatomy of the human body. Consequently, the zoom range of the outcomes is between the lowest level of aggregation that is possible (zoom-in) and the entire temporal or geographical scope (zoom-out).

Conditions The conditions perspective is about connecting agent performance to the conditions it is situated in. This requires the data to contain performance attributes at the lowest level of aggregation, as well as attributes describing the (environmental) conditions at the same level. In many cases, the complete set of attributes (containing both information about the performance as well as information about the influencing conditions) for a given problem requires integration of multiple data sets. Hence, it is prerequisite that each of the sources have the same lowest-level aggregation base. For example, data about the weather conditions should be available at the same detail level as the data about how a system performs, for example the number of traffic accidents on a road network. Furthermore, performance-related attributes may have to be computed based on physical or empirical relations applied to a particular data source, for example, the collision energy in a traffic accident may be derived from the initial driving speeds. Evaluation of the conditions perspective is often made using using data-science techniques like regression models and data mining approaches, regularly utilising machine learning. The availability of attributes in the evaluated data is key for the potential of relations between agent performance and conditions that can be established by these techniques.

Behaviour The behaviour perspective requires that the data enables identification of agents, that can be linked to their movement in space or evolution in time. For example, the concept of moving features keeps track of an object with certain properties, as a function of time and space (Asahara et al., 2015). An agent can be a physical individual, such as a car, a ship or a human being, or a collective that acts as ’one’ on the lowest level of aggregation in the data. Practically, this means that on the corresponding level, the data should provide information on the identity of the agent. It should also be traceable what the sequence of actions of individual agents was, hence, the scale-perspective requirements should be fulfilled. Agent-based models have similar characteristics when it comes to the principles they use to achieve their outcomes. Many studies that we indicated above as behaviour-perspective examples, have used agent-based models. Basically, the information required to determine the behaviour of the agents in the models, is equal to the outcomes that can be provided when evaluating the underlying data from the behaviour perspective.

Dependencies The highest-level complexity perspective is that of dependency. Only relying on real-world data is most frequently not sufficient to evaluate the system from this perspective. It aims at understanding the causal relationships; understanding how actions of (an) agent(s) are initiated by or dependent on actions of (an)other agent(s). These outcomes require running of a model, to investigate the causalities between different processes, while validating the outcomes using real-world observations. Techniques often used to do this are for example Bayesian (hierarchic) networks or dynamic models. Although dynamic models intend to focus on high-level processes only, they strongly rely on dynamic variations in time to investigate causal relationships.

Perspective	**Requirement**	
Scales - Understand 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 (meters, street/city/country level, etc.)
	Aggregation means	For deriving time aggregates (hours, days, weeks, months, etc.) For deriving spatial aggregates (street, river, area, state, etc.)
Conditions - Understand the effect of external conditions on the performance of agents and the total system	Fundamental components	The resolution of the specified external/environmental conditions
	Condition variables	Attributes indicating the conditions and coupling these to performance
Behaviour - Understand the influence of the sequential actions of individual agents or collectives on the performance of the system	Fundamental components	Identification of individual agents or collectives
	Activity sequence	Attributes tracking the sequence of activities performed by an agent (or collective)
Dependencies - Understand critical paths and sensitivities in the system due to reliance of agent's actions on other agents	Initiations	Dependency of an event on (an)other event(s)

Table 2.1: Framework perspectives used to define upfront analyses requirements

2.2.3. Integration of perspectives into one data concept

The objective of our framework is to guide the design of a conceptual model for multi-perspective system analysis, by (1) supporting pre-analysis selection of input materials (data and tools), and (2) guiding the design of a data structure that facilitates incorporation of multiple discipline-specific concepts into a single data structure. By connecting the analysis objectives for each perspective to the corresponding requirements in Section 2.2.2, the first part of the framework is presented in Table 2.1. For distinct cases, this supports the design of a conceptual model, whereby its complexity depends on the case and the chosen perspective(s) to consider. The second part considered the design of a suitable data structure. Hereby, we found two existing concepts jointly serving as a basis for the development of such a structure: event logs and moving features.

Event log In the field of process mining, event-based data in the form of an event log is used to assess the overall performance and compliance with business processes. An event log is a collection of events, where each 'event' is defined by its 'case' and its 'activity'. The case, or process instance, indicates 'what process the event is part of'; for example a patient's care process in a healthcare system (Mans et al., 2009) or the process of a person's invoice in an organisation (van der Aalst, 2012). The activity, or task, is 'a well-defined step in the process' or 'action conducted by someone on the particular case'; for example conducting a check, referring the patient, or signing for approval. In addition to the case and the activity 'event attributes' may provide additional information about each event, such as the duration, the performer or executor, or other case details (van der Aalst et al., 2003; van der Aalst, 2012; Dakic et al., 2018).

Moving features Moving features are a concept to keep track of a feature, viz. an object with properties, as a function of time and space (see e.g. Asahara et al., 2015). In addition to the time and space information 'attributes' may provide additional information about the object, for example related to identity or dimensions.

Table Data organised in table format consist of rows and columns. Hence, each record contains the same fields.

In the descriptions in Section 2.2.2 and Section 2.2.2, we described the behaviour of an individual agent as a sequence of *actions*. Following the approach used in process mining, we use *event* to indicate one action undertaken by a specific agent, whereby the conditions and characteristics of that action are known. Following the moving-features concept, these action characteristics provide temporal and spatial information about the agent, enabling tracking in time and space. Hence, an *event* is one action undertaken by a specific agent, at a moment or period in time, a point, segment, or area in space, under certain conditions, and having particular characteristics. Our considered system is represented by the collection of all events that are part of it. Unlike these two concepts, our data structure adapts a tabular structure, since this facilitates performing sorting and filtering operations. Our new concept is therefore referred to as an "event table". Herein, each row represents a distinct event, and each column indicates a characteristic of the event. Table 2.2 presents how the event-table concept was composed of event log (EL), moving features (MF), and general table (T) characteristics. In the event table, the rows define how fine-grained the events are, i.e., what kind of basis, or fundamental components, do we use to distinguish one event from another? The columns prescribe which trends can be extracted, i.e., what kind of variables can we use to aggregate or filter by? Hence, a unique event is characterised by event-defining columns, basically jointly forming the index of the table. (For the event log, the case and activity are the event-defining columns.) The attribute columns provide additional information about an event.

As indicated in Table 2.2, the tabular structure provides the capability to sort, filter and aggregate the data (for each perspective). To achieve this for the scales perspective, required a hierarchic spatial structure (grid, network, graph, etc.) with a finite number of location categories (cells, nodes, edges, segments, etc.). These categories must be at least of the scale of the prescribed spatial fundamental component, to facilitate that random points in space (for example, describing trajectories of agents) can be allocated to these categories. Subsequently, a single event covers a single *spatial category*. How an event is defined exactly for a given application case, depends on which perspectives are considered. The specifications for the fundamental components of the scales, conditions and behaviour perspectives drive how a single event is defined (for example, using spatial category, temporal indicator, environmental condition, and agent identity), determining the length of the table. The other specifications represented in all four perspectives, drive which attributes describe an event, thereby determining the width of the table.

Perspective	Requirement	MF	EL	T	
Scales	Fundamental components	✓	✗	✗	Combine MF capability to track positions and tabular operations. Practically, for each event, we store the *spatial category* as part of a hierarchic spatial structure.
	Aggregation means	✗	✗	✓	
Conditions	Fundamental components	✓	✓	✓	Each concept uses attributes, however, EL have varying attribute sets per event, and MF ties them to an object. We use a table for sorting, filtering and aggregating.
	Condition variables	✗	✗	✓	
Behaviour	Fundamental components	✓	✓	✗	Adopted from EL, each event is characterised by its *agent identity*, and the sequential order of events is stored in the *instance* column.
	Activity sequence	✗	✓	✓	
Dependencies	Initiations	✗	✓	✗	We keep track of previous and following events in the attribute columns, like in EL.

Table 2.2: Traits of the event log (EL), moving features (MF) and table (T) concepts that fulfill the requirements for the event table concept

2.3. Nautical system framework applications

To demonstrate how representing a system by an event table introduces a new degree of flexibility to evaluate it, we use three shipping-related examples. In each of them, vessel position data through AIS were available. The challenges were to couple this source to other data sources and methods at the right level, and to apply a concept allowing for extraction of multiple perspectives on the system. The first example considers shipping emissions on inland waters, whereby the objective is to find effective emission-reduction measures (also see Chapter 5). The second example considers nautical safety, aiming at understanding what determines the distance vessels keep in ship-ship encounters (Baak, 2023). The third example focuses on lock operations, having the goal to optimise lock processes and to decrease waiting times (Kuiper, 2023).

Figure 2.3 presents the main steps to apply the introduced framework to a specific case, starting with defining the objectives for each perspective. We use the introduced framework to specify the corresponding requirements for our event-table concept. Subsequently, these requirements are united into a case-specific concept design, driving the identification of data sources and approaches that are required to achieve the objectives. The event table design is the basis for the output shape of analysis, modelling, or calculation processes that become the content of the event table. Outcomes from any perspective can finally be extracted from the single event table. The case examples demonstrate how the different perspectives relate to and complement each other.

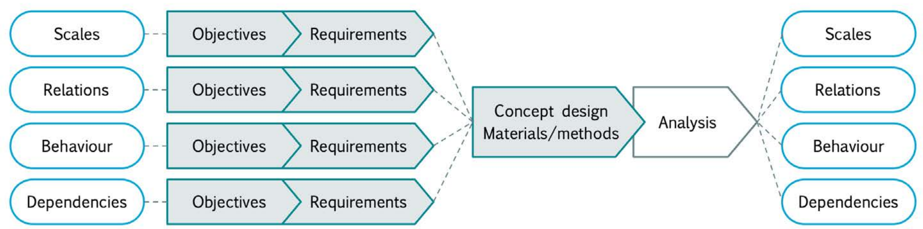


Figure 2.3: Schematisation of how the framework is applied to a specific case.

2.3.1. The case of inland shipping emissions

Various approaches exist to estimate shipping emissions based on the velocity tracks of a vessel captured by AIS data. By using the introduced framework, the decision making for the applied approach and data sources are supported. The first column in Table 2.3 presents the defined objectives per perspective for the first case. Based on these objectives, requirements for the event table were formulated, as also indicated in the table.

From a scales perspective, emission maps, indicating spatial patterns and the most important hotspots, were desired. The spatial fundamental components, determining how far we can zoom in, were chosen to be fairway segments. These segments are the spatial categories of the hierarchic spatial structure for aggregation: a graph representing the fairway network. Since a vessel may cross a fairway segment in under a minute, the temporal fundamental components were set to seconds. From a conditions perspective, the objective was to relate the magnitude of emissions to the environmental conditions wherein the vessel operates, as well as the size and shape of the vessel. Hence, this requires data on fairway properties like the water depth and current velocity. Intermediate calculation outcomes are required to further understand potential causes of high emissions, based on the derived trends. The behaviour perspective considers how actions of the captain influence the emissions (in contrast to the physical design parameters of the ship, which is covered by the conditions perspective). For example, when approaching a lock, different captains may reduce speed at different distances from the lock area. In order to tie this to the emission levels, requires knowing the vessel identity for each event, as well as the sequential order of events 'executed' by one vessel, for which time stamps are used. The influence of actions of one vessel on the emissions of another vessel, as regarded under the dependencies perspective, was not considered.

Knowing the requirements for individual perspectives in Table 2.3, we can define the design of the event table that fulfills them jointly. The definition of a unique event is formed by the combination of the fairway segment where the vessel is sailing, the vessel identity, and the start time of the event. Hence, the number of events, equalling the number of rows in the table, corresponds to the number of unique combinations of *fairway segment*, *vessel identity* and *time stamp of event start*. Aside from these event-defining columns, the attribute columns should be specified. These columns provide the details for each event, being among others the water depth, current speed, vessel length, width, draught, and all emission estimates. Furthermore, we need all intermediate calculation outcomes to be stored in the attribute columns.

What does this mean for the materials and methods? For data sources, we require that all information about the (occurrence of) emissions, to be stored as attributes in the table, should be available the specified level of detail. This means that water depths should be (made) available for individual fairway segments, as well as current speeds. Vessel properties are most logically coupled to a vessel identity, however, the vessel draught may vary from journey to journey. Regarding the method to determine emissions, the requirements in Table 2.3 drive the choice for an approach that can take into account the influence of the specified influencing factors. For example, not every approach considers the water depth to influence the vessel emissions.

The analysis for this case mostly regarded the assignment of points on each AIS-track to distinct fairway segments, and the calculation of emissions based on all input variables. All intermediate results as well as the estimated emissions were added to the event table as attribute columns. Based on this outcome, multiple perspectives could be evaluated. From a scales perspective, aggregation by fairway segment resulted in quantified emission patterns presented on a full-scope map, also indicating important hotspots. From a behaviour perspective, the influence of the engine power setting could be quantified for the identified hotspots, uncovering two distinct causes: idling vessels and fast sailing vessels, both having a disproportionate contribution to the emissions.

Objectives	Requirements	
Scales - Zoom out to spatial patterns of inland shipping emissions and zoom in to hotspots, evaluate temporal patterns	Fundamental components	Seconds Fairway segment
	Aggregation means	Fairway graph
Conditions - Understand the influence of the environmental conditions on the emissions	Fundamental components	Water depth, current speed, vessel main dimensions
	Condition variables	Intermediate calculation outcomes
Behaviour - Understand how vessel behaviour contributes to the emissions	Fundamental components	Vessel identity
	Activity sequence	Time stamps
Dependencies - Not considered	Initiations	-

Table 2.3: Framework perspectives used to define analysis requirements for emissions of the inland shipping system

2.3.2. The case of distance keeping in ports

This case considered an evaluation of the distance keeping between vessels in ports, with the objective to understand which factors influence how far two vessels stay apart. This understanding is required for timely safety interventions as well as for the development of autopilots and Maritime Autonomous Surface Ships (MASS). The first column in Table 2.4 presents the defined objectives per perspective for this case, as well as the corresponding formulated requirements. Hence, the most important perspectives considered are conditions and behaviour.

From the conditions perspective, the objective was to determine the influence of local circumstances; how does the waterway or port area design, for example channel width or presence of crossings, influence the distance-keeping between vessels? Similarly, from the behaviour perspective, the influence of the maneuvering type and the relative vessel speeds were of interest. On one hand, this required attribute data on the environmental conditions, as well as details on the encounter, like relative distances, headings, and velocities, and on the other hand it required keeping track of the identities of all encountering vessel pairs. From the scales perspective, we want to be able to zoom in on individual encounters and aggregate for various port sectors. Consequently, the event-defining columns of the event table for this case are *vessel identity 1*, *vessel identity 2*, and *time stamp*, whereby the unique combinations determine the number of events. The attribute columns are among others the location, port sector, vessel paths, distances, headings and velocities, as well as properties of both vessels.

Derived from the generated event table, the scales perspective revealed the higher encounter frequency between ships in port areas with more crossings (refer to Figure 2.4). We could connect this with the behaviour perspective as well; besides more encounters, the absolute distance between encountering vessels was much smaller, and their relative headings indicated relatively less overtakings and more cross-encounters.

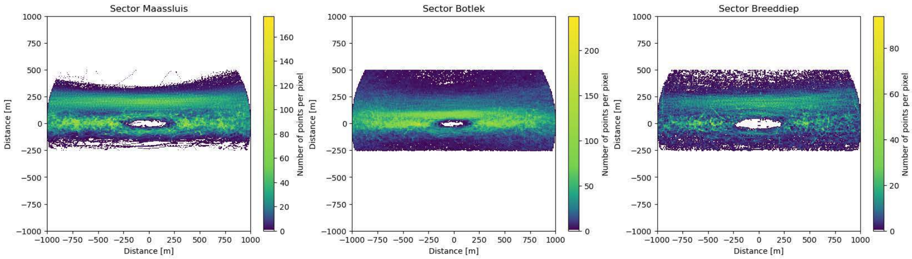


Figure 2.4: Ship domain indicated by intensity plots of encounters for three sectors in the Port of Rotterdam: Maassluis (straight waterway without crossings), Botlek (intersection with maneuverings) and Breeddiep (hotspot with combined marine and inland traffic). Figure by Baak (2023).

In general, from the conditions perspective, it was found that the largest vessel dimensions, as well as the relative speed between the vessels, were the most important factors determining how much distance was kept (Baak, 2023).

Objectives	Requirements	
Scales - Zoom in and out on spatial patterns of encounter density, types and ship domains	Fundamental components	Seconds Single vessel-vessel encounter
	Aggregation means	Port area subdivision into sectors
Conditions - Understand the influence of local circumstances on vessel-vessel distance	Fundamental components	Current speed, vessel dimensions
	Condition variables	(Relative) headings, angles, distances, velocities
Behaviour - Understand how vessel speed and relative position influence vessel-vessel distance	Fundamental components	Keep track of both vessel identities
	Activity sequence	Time stamps
Dependencies - Not considered	Initiations	-

Table 2.4: Framework perspectives used to define analysis requirements for the distance-keeping case in a port area

2.3.3. The case of lock process efficiency

As lock passages may take up to a third of the total travel time of an inland vessel (Hekkenberg et al., 2017), there are evident benefits to optimise lock passage processes. Furthermore, the trend of more extreme water level variations in rivers and channels calls for optimised lock operation strategies to ensure sufficient fresh water availability for drinking and irrigation (F. Bakker and van Koningsveld, 2024). This third case therefore had the objective to evaluate the efficiency of lock passage processes for locks on Dutch inland waters. The objectives were formulated more specifically according to the perspectives, as presented in the first column of Table 2.5. The corresponding requirements for the event table are specified in Table 2.5 as well.

To understand what determines the passage times, and how this results in different performance from one lock complex to the other, requires an analysis up to the detail level of different phases in the locking process. How are the passage times composed of waiting time before entering the lock, time to enter and moor, and leveling time? This drives the requirement for the scales perspective, that the fundamental component is a single phase in the locking process (which is both a spatial and a temporal specification). To aggregate this to a mutual comparison between lock complexes, requires an aggregation structure that linking them, hence, logging the lock phase, cycle, chamber, and complex. Based on these scale-related requirements, the influence of physical conditions in individual lock phases on the duration of each phase can be evaluated: How do the lock process durations change for changing water level differences, and what is the role of the discharge rate of the lock? This requires tracking of these variables, and having this data available, if applicable at the appropriate time intervals. The behaviour perspective takes a view from the vessels (how long do vessels have to wait depending on other vessels) or from the operator (how are overall waiting times influenced by alternative operating strategies). In this case, the dependencies perspective is relevant, as the waiting time of one vessel can be influenced by the lock passage time or arrival time of another vessel. Therefore, it must be possible to link subsequent activities (of different vessels) to each other. More specifically, it is needed to track the entering sequence of the vessels (who came first, etc.).

Based on the outlined requirements, the events are defined by the *vessel identity*, *lock cycle identity*, and *lock phase*, stored as the event-defining columns in the event table. The attribute columns are among others the duration of the event (locking phase), the lock chamber identity and dimensions, the lock complex, water level difference, discharge rate, and vessel properties. The main data processing regarded identifying vessels, creating trajectories, distinguishing lock chambers and lock stages from the AIS data, based on the layout of the lock complex, as described by Kuiper (2023). By binning and aggregating for discharge rates, the objective from the conditions perspective can be evaluated, quantifying its effect on the passage times of vessels for different locks. From the dependencies perspective, we could aggregate based on the vessel's position in the arrival sequence. Based on this, it was possible to quantify the additional passage time for a vessel arriving first in a sequence of two, compared to that of a vessel arriving second in a sequence of two.

2.4. Discussion of the multi-perspective framework

With the presented shipping system cases, we demonstrated that it is possible to combine multiple disciplinary concepts into a single conceptual model. One of the opportunities that this offers, is that the system can be viewed both spatially (the *scales* perspective in our framework), as well as from a process-oriented (*behaviour*, in terms of our framework) perspective, considering coherence between sequences of events and system performance. This is important, since many problems require understanding of both the "where", and the "how". For example, in the emissions case (1), to understand how captains respond to changing fairway conditions, it is required to connect the sequential actions of individual captains to the varying conditions they encounter on their route. In the nautical safety case (2), it is necessary to know the locations of

Objectives	Requirements	
Scales - Understand time-distance relationships and waiting times per location	Fundamental components	Phase in locking process
	Aggregation means	Locking cycles - lock chambers - lock complexes
Conditions - Understand the influence of lock design and local circumstances	Fundamental components	Water level difference, discharge rate, chamber size, vessel properties
	Condition variables	Relative time windows of individual vessels
Behaviour - Understand how lock operating approach influences waiting times	Fundamental components	Keep track of vessel identities per locking cycle
	Activity sequence	Time stamps
Dependencies - Identify causes of (extreme) waiting times	Initiations	Link with activities in same locking cycle as well as previous and subsequent cycles

Table 2.5: Framework perspectives used to define analysis requirements for the locking process case

small distance encounters, as well as the type of encounters, to understand the best nautical traffic management measures to improve safety. These examples emphasise the importance of evaluating these perspectives cohesively, instead of looking at them separately.

The presented framework supports the upfront selection of data sources and (simulation) models, as well as the incorporation of multiple disciplinary concepts into a single conceptual model. Given the different worldviews of different analysts, using our framework means that each of them would design a single conceptual framework for their system analysis, but it does not necessarily mean that they would all design the same conceptual model. Their considerations for accepting or rejecting available input materials may still be different, however, the framework offers the necessary transparency around their decisions. Furthermore, the framework is meant as a support in the balancing act between achieving defined analysis objectives, and the availability of materials (data and tools). In many cases, the materials required to achieve certain goals are not readily available, or not available at the desired scope or resolution. The role of our framework is to make these considerations explicit, before starting the analysis. Based on this, a well-supported decision can be made to either put effort in making the required materials available, or to make concessions about the defined analysis goals.

Even when considering only one source of data in an analysis, pre-analysis considerations as suggested by our framework can prove valuable. Graser et al. (2024) investigated the data representations for trajectories that were used for training of deep learning models, distinguishing between individual and aggregated levels, observing that raw trajectory data were mostly converted into " more compact representations of individual trajectories (sparse trajectories) or aggregations of multiple trajectories." These choices strongly relate to the analysis objectives (in our framework, considering the *scales* perspective), forming the system representation. As Siegenfeld and Bar-Yam (2020) indicated based on molecule trajectories: "The behaviors that distinguish solids from liquids from gases are examples of emergence: they cannot be determined from a system's parts individually." One of the challenges addressed by Graser et al. (2024) is the difficulty to evaluate and compare models, "due to different datasets and applied metrics". Explicit consideration of data sources and fundamental components in the system representation, as done in the framework, can help setting and documenting benchmarks.

Similar approaches can be found in other applications. For temporal-data visualisations, Bach et al. (2017) described a range of elementary operations on a "generalised space-time cube", whereby "any space-time cube can be subdivided into lower level space-time objects". This model supports creation of a single concept that holds all relevant data about a system, up to the most detailed required object level. In software development, Gupta et al. (2023) selected a consistent and complementary set of conceptual models for requirements analysis and system design based on a set of user stories expressed by multiple perspectives. The difficulty is in how to integrate these different conceptual models. In ML, a field wherein many data sources are interchanged, this is also point of attention. eXplainable Artificial Intelligence (xAI) refers to the "details and reasons" a model provides to make transparent how it works (Barredo Arrieta et al., 2020). For neural networks this is mostly achieved by feature relevance techniques. As an alternative, an event table could serve as a basis for feature engineering in ML approaches, enabling pattern discovery by ML algorithms, while using the connection between raw data and outcomes to support the algorithm results. A similar starting point has been used by Kanter and Veeramachaneni (2015) to develop an approach for automated feature engineering. Hereby, different "depths" (similar to "object levels" in Bach et al. (2017)) were identified to generate features based on direct or aggregated relations between these depth layers.

2.5. Chapter conclusions

The increasing complexity of the real world drives a search for integrated solutions that are supported from multiple perspectives. The main focus in this chapter was to achieve an integrated view of a system, without knowing exactly upfront which information is required from the different perspectives. The developed framework supports the assembly of a data structure that allows evaluation from various perspectives, from different domains and disciplines.

This flexibility is achieved through consideration of the four proposed perspectives - scales, conditions, relations, dependencies - during the assembly process. The framework hereby provides guidance for the selection of data and the formulation of analysis concepts. The application cases in the nautical field demonstrated how this process can be put into practice and how the various concepts can be merged into a single data structure. Consequently, it enables linking system-level patterns and performance to detail-level processes and underlying data, and linking observations and outcomes based on one perspective with those of other perspectives. As such, the framework can be used to anticipate new perspectives in the future.

3

Data-Science Techniques Striving for Real-Time Maritime Safety Monitoring Support

Birds go flying at the speed of sound
To show you how it all began
Birds came flying from the underground
If you could see it then you'd understand

Guy Berryman, Jonny Buckland, Will Champion, Chris Martin

The perspective-related requirements formulated in Chapter 2 facilitate a thorough consideration of the (im)possibilities regarding analysis goals in view of available data, analysis tools and calculation facilities; they do not demand the most advanced analysis techniques necessarily. However, by drastically improving computational performance, the integration of multiple perspectives into a single analysis becomes possible. This brings real-time data analysis a step closer, which is important for among others safety monitoring of nautical traffic. Therefore, research question 4 considers: ***How can data-science techniques broaden the applicability of the perspectives in the framework for nautical safety monitoring at the Dutch North Sea?***

This chapter incorporates work from the following publications:
S. van der Werff, F. Baart, and M. van Koningsveld, *Vessel Behaviour under Varying Environmental Conditions in Coastal Areas*, 35th PIANC World Congress, 29 April – 3 May 2024, Cape Town, South-Africa (2024)
S. van der Werff, F. Baart, and M. van Koningsveld, *Zoomed-Out Corridor-Level Shipping Emissions, Zoomed-In Ship-Level Causes, and Everything in between*, 35th PIANC World Congress, 29 April – 3 May 2024, Cape Town, South-Africa (2024)

3.1. Maritime coastal monitoring support

Several incidents in the North Sea and Baltic Sea over the past years have highlighted risks of the intense and multi-purpose use of this area, hosting extensive infrastructure cable and pipeline networks, oil and gas platforms and wind parks, and while being an important and delicate environment for marine and other species, shipping activities take place here, additionally. On the 1st of January, 2019, container vessel MSC Zoe sailed through rough conditions, with strong gales and wave heights of over 5 meters (Umar et al., 2020; Krüger and Jannsen, 2020). The roll motion of the vessel caused the loss of 342 containers in the North Sea North of the Island Terschelling, leading to environmental damage, particularly in the protected Wadden area (van der Molen et al., 2021; Herman et al., 2021).

On the 31st January, 2022, dry-bulk vessel Julietta D. suffered from a mooring system failure in storm conditions, sending the vessel adrift from the anchoring area West of IJmuiden in the North Sea. During its drift, it collided and caused damage to another vessel at the anchorage, as well as a platform under construction, and a wind turbine foundation (Umar et al., 2024). On the 26th of September, 2022, following suspicious presence and actions of a sailing vessel, multiple underwater explosions occurred on pipelines in the Baltic Sea, causing gas leaks and leaving them inoperable (Botnariuc et al., 2023). In November and December, 2024, several disturbances and damages were reported related to submarine cable infrastructure in the Baltic Sea, which were linked to suspicious presence of commercial vessels (Ahlander et al., 2023; Kauranen, 2025).

While having different root causes, these incidents all occurred at the interface of multiple functions that the North Sea fulfills, e.g., shipping, infrastructure, and nature. As a result, the consequences of these incidents can be (very) large. Besides precautionary measures to improve ship design and integrity and navigability of shipping lanes (Umar et al., 2020; Krüger and Jannsen, 2020), increasing the probability of a timely intervention in each of the examples can reduce these risks. In case of severe weather, early detection of vessels exposing signs of extreme motions may be guided into safer courses, speeds, or waters, before suffering from cargo loss. Early detection of drifting vessels may reduce collision or allision risks by alarming nearby traffic and fast mobilisation of support and towing vessels. Finally, early detection of suspicious behaviour can reduce the probability or the severity of the consequences of sabotage, by having authorities at the site sooner. Hence, to increase the effectiveness of interventions, a fast detection of the incident by the responsible authorities is required (Chandola et al., 2009; Riveiro et al., 2018).

An incident generally stands out because of unusual, anomalous actions or behaviour, whereby the location and conditions under which the incidents occur, may play a role (Lane et al., 2010; Tu et al., 2018). The term *anomalous* is broad and refers to anything that does not conform to a defined *normal*. Chandola et al. (2009) defines *anomaly detection* as "the problem of finding patterns in data that do not conform to expected behaviour". In this way, fraudulent, suspicious, or malicious behaviour may be uncovered through anomaly detection. In the field of maritime safety and security, anomaly detection could be used to identify behaviour exposed when a vessel has maneuverability issues, is adrift due to a technical failure, or when it is potentially

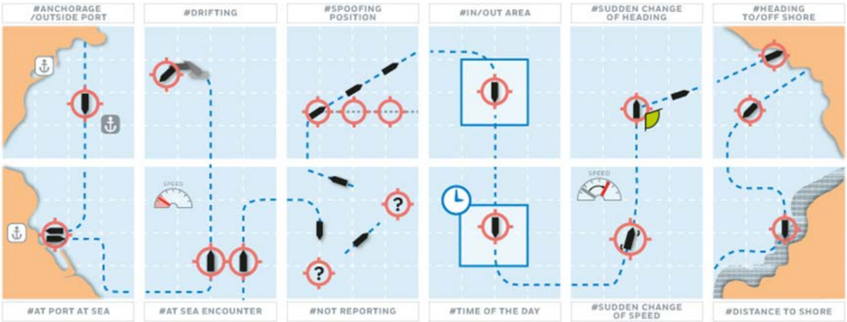


Figure 3.1: Behaviour pattern categories for Automated Behaviour Monitoring (ABM) used by European Maritime Safety Agency (EMSA)

conducting malicious activities, similar to the incidents described above.

The main distinction between the various approaches to detect anomalous shipping behaviour is between rule-based approaches (also referred to as knowledge- or signature-based approaches), data-driven approaches (including statistical, machine learning, data mining) (Sidibé and Shu, 2017; Riveiro et al., 2018), and hybrid approaches. Rule-based approaches require predefining vessel behaviour patterns using rules and threshold values, to extract anomalous behaviour that complies with these categories. Hence, the detected behaviour should be known. For example, Lane et al. (2010) defined five categories of anomalous vessel behaviour based on AIS data, being route deviation, unexpected activity, unexpected port arrival, close approach, and zone entry. Another example is presented in Figure 3.1, being the distinguished behaviour pattern categories for ABM by EMSA. Related to each of the categories, different rules and threshold values have been developed to identify behaviour in this category (Roy, 2010; do Nascimento et al., 2024).

Data-driven approaches on the other hand, do not specify rules, but evaluate the totality of available data, for example, AIS points or tracks, to generate a normal shipping pattern (normalcy model, see Brax (2011)), and to determine if a single (new) observation is a normalcy or an anomaly (Ribeiro et al., 2023). Consequently, no upfront knowledge about the expected behaviour is needed. Clustering techniques have been used to classify vessel movement patterns based on AIS-trajectories, using Density-Based Spatial Clustering of Applications with Noise (DBSCAN) (Daranda and Dzemyda, 2020; Widyantara et al., 2023).

Owing to these developments, important steps have been taken towards identifying anomalous behaviour of vessels, however, thus far, this has not resulted in useful, real-time support can be provided to vessel traffic monitoring operators. The aim of this Chapter is to identify and tackle important data-science challenges on the path to real-time monitoring support. Identification of the most important challenges is done based on the framework for system analysis developed in Chapter 2, that considers a system from the four perspectives scales, conditions, behaviour and dependencies.

For each perspective, based on analysis goals, the framework provides guidance for the selection of data sources and input materials, and the design of a data concept. In this chapter, this is supplemented with data-science techniques that are needed to tackle the identified challenges.

3.2. Data-science challenges

The framework presented in Chapter 2 consist of four perspectives for system analysis, being scales, conditions, behaviour, and dependencies. By considering each of these perspectives in a system analysis, the framework aims to provide structured requirements for the representation of the system with a data structure and for the selection of input materials, in view of the analysis objective. Table 2.1 provides an overview of how the analysis goal is considered from the four perspectives, and the concurrent requirements to the input materials and data structure. One of the benefits of the framework is that forthcoming requirements that are unrealistic can be identified upfront of the analysis. Appropriate action can then be taken, either by adapting the objectives, or by increasing the effort to gather the required input data and tools. In this section, challenges related to tools, and data-science specifically, are identified for each perspective. In the subsequent sections, data analysis and processing tecnhniques are proposed to tackle these challenges.

The Scales perspective ensures that the system can be considered from various zoom levels, and that these levels stay interconnected. It addresses the scope and resolution of the input data sources, and the spatial hierarchic structure that couples the detail levels to the global levels. Combining a large scope with a high resolution, needed when monitoring individual vessels in large coastal areas such as the Dutch North Sea, demands large computational efforts. *Scalability*, e.g. fast processing of large amounts of data, is regarded as an important challenge (Sidibé and Shu, 2017; Riveiro et al., 2018; Ribeiro et al., 2023), that currently hampers achieving a real-time pace.

The Conditions perspective considers the role of underlying processes and their environment, focusing on identifying relevant influencing factors and environmental parameters. Most approaches for anomaly detection focus on the vessel trajectories and related data in AIS only (Sidibé and Shu, 2017; Tu et al., 2018), although the specific context, may be crucial to determine whether a manoeuvre is anomalous or not (Alessandrini et al., 2014; Venskus et al., 2019; Rong et al., 2024). This contextual data, for example the area a vessel is located in (e.g., open sea, anchorage, or port) or the environmental conditions it encounters (e.g., limited sight, strong wind, or calm sea) is likely to be available as open source (Kazemi et al., 2013). To understand how a system in general is influenced by the conditions, context, or environment it operates in, is regarded as an important remaining challenge (Lukyanenko et al., 2022). Related to this, (Riveiro et al., 2018) "observed a lack of studies regarding feature extraction and finding relevant features in high-dimensional maritime datasets", hence, addressing the decision-making around which information to incorporate. For the purpose of detecting anomalous vessel behaviour, multiple input data sources are needed. Section 3.3.1 discusses joining multiple relevant input sources and extracting the relevant information in the form of features.

The Behaviour perspective evaluates the behaviour of individual agents or collectives. This is the subject of most maritime anomaly-detection approaches, mostly making either point-based detections or trajectory-based detections (Pallotta and Jousselme, 2015). Point-based detections focus on identifying individual anomalous points, for example, as part of an AIS-track, whereby clustering techniques are commonly used. Trajectory-based detections focus on determining the similarities between entire trajectories by comparing their shape. Many of the existing approaches produce many identified anomalies, whereof a large share being false alarms (Laxhammar and Falkman, 2015; Radon et al., 2015). However, to be of support in real-time monitoring, it is important to take into account the cognitive load on the VTS operator (Riveiro et al., 2018), raising the challenge to present the outcomes in a meaningful way to the operator, minimising the distraction from their work routines. Related to that, an operator needs to be able to judge an potentially take action upon an anomaly rapidly. Jointly, this requires the ability to unfold behaviour, i.e., all relevant information about an identified anomalous track to be available to the operator (van den Heuvel, 2024).

The Dependencies perspective considers interdependencies between different agents and events. A simple example is when a vessel deviates from its course to overtake another vessel, or to reduce speed to give way at an intersection. In our monitoring case, this manifests itself through a chain of interrelated events that lead to some incident. How do we determine whether two events are interrelated? To understand this, we need to label each of the considered events. Based on the labelled dataset, it is possible to distinguish chains of events that form patterns demonstrating their dependencies.

Summarising, the identified challenges on the road towards real-time monitoring support for vessel traffic monitoring operators, are as follows:

Scales Scaling-up of computations

Conditions Incorporate the role of environmental and local factors

Behaviour Unfold detected outlier behaviour

Dependencies Label and classify known behaviour

3.3. Perspectives on data science to improve anomaly detection

The proposed anomaly-detection approach addresses the identified challenges for achieving real-time monitoring support. A high-level flowchart of the approach is presented in Figure 3.3, following the approach of van Engelen (2023) and van den Heuvel (2024). To anticipate anomaly detection of unseen behaviour, a data-driven approach is used. The first challenge, of scalability, is addressed by the *Trajectorise* function, introducing a parallellisation technique that is applied to process the large amount of data into a large-scope visualisation of patterns at a high detail level, and that can furthermore be used to perform parallel computing on trajectorised AIS data. This is further described in Section 3.3.1. To connect to the context, e.g., the Conditions-related challenge, the data sources are joined, meaning that the instantaneous conditions are coupled to the location and time span of each considered trajectory. This

Figure 3.2: Map of the Dutch part of the North Sea, indicating the considered area

is part of the *Join-data* function. Furthermore, features, representing both the trajectory characteristics and the conditional information, are extracted from this comprehensive dataset in the *Engineer-features* function. Both functions are described in Section 3.3.2. The next challenge is to detect anomalies based on this extensive set of features, as part of the Behaviour perspective. This is done in the *Dim-red-clustering* function, by conducting dimension reduction before moving to a clustering technique to identify anomalies. Refer to Section 3.3.3. Finally, as part of the Dependencies perspective, Section 3.3.4 presents how labeling of data provides the next step towards recognising incidents and accidents.

The data sources used in this study are as follows:

Dutch Government Data Register (DGDR) Geometry coordinates for spatial features at the North Sea provided exact locations of Traffic Separation Scheme (TSS), approach areas, anchorage areas and wind parks (Dutch Government, 2023).

AIS data Following the International Maritime Organisation (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, ranging between the North of Amsterdam (52.55 degrees North) and the South of Tweede Maasvlakte, Port of Rotterdam (51.85 degrees

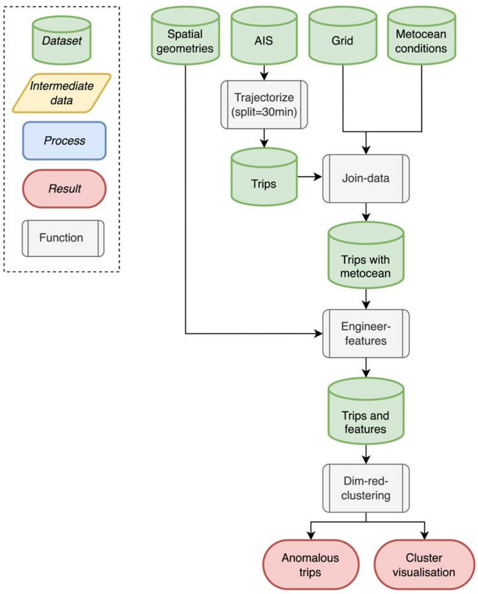


Figure 3.3: Flowchart presenting an overview of the anomaly-detection approach

North), refer to Figure 4.3. We used data of 31 January and 1 February of 2022. 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. Cargo vessels were considered only, by filtering out *vesseltypes* with values between 70 and 99.

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. We used data of 31 January and 1 February of 2022.

MATROOS Tidal and wind-driven currents were considered, that were retrieved from *MATROOS*. Northerly and Easterly velocity components were used in the analysis. We used data of 31 January and 1 February of 2022.

3.3.1. Scales: computational scale-up

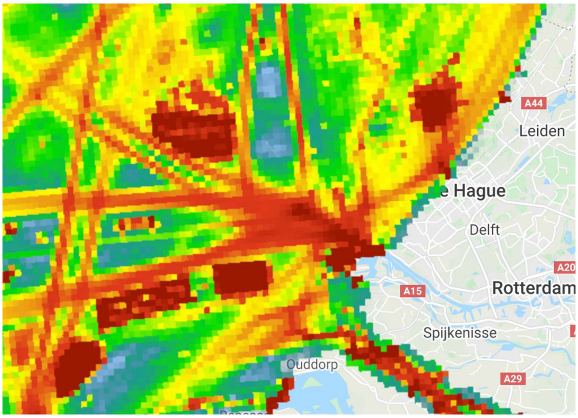
A key feature of the multi-perspective approach is to explicitly keep the connection between the large scale and the small scale, enabling visualising the system-level patterns (zooming out) as well as the detail-level patterns (zooming in). This is defined by the Scales perspective in particular. The formulated requirements in Table 2.1 provide guidance for the decision-making around this theme, weighing in available data sources, analysis or modeling approaches, and computation facilities.

In many studies, driven by computational constraints, the focus is either on (aggregated) large-scale patterns, or on smaller-scope detail patterns. In view of coastal analytics, Calkoen et al. (2025) refers to these analysis strategies as "everywhere versus anywhere". Examples of large-scale shipping patterns, in the North Sea coastal area near the Netherlands, are presented in Figure 3.4. Each of them clearly reveals the high-level shipping patterns, indicating among others the main shipping lanes along the coast and into the port of Rotterdam, the anchorages, recreational shipping near the coast, and areas with limited shipping activities. The visualisations differ in the level of detail that is displayed, whereby Figure 3.4a, Figure 3.4b, and Figure 3.4c have increasing resolutions. By presenting aggregated densities at a grid size of several kilometres, maps like Figure 3.4a have detached the large-scale patterns from the underlying (detail-level, raw) data. Consequently, these patterns cannot be connected to causes that are part of detail-level processes. Although both high-level and detail-level approaches succeed in their distinct objectives, being able to flexibly zoom in and zoom out, using the same basis, enables connecting large-scale and detail-level patterns, improving the ability to explain either of them.

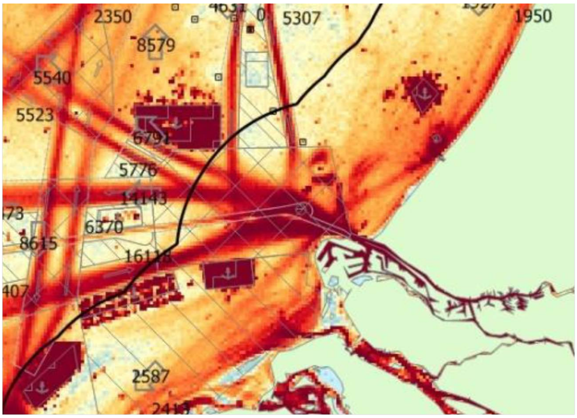
Serial to parallel computations

To achieve this zooming capability while relying on large amounts of data requires scaling-up *computationally* (if calculation time is not unlimited). A common way to improve computational performance is to identify computational processes that are suitable for running in parallel. Plotting position data of large data sets is such a process. Figure 3.5 presents the workflow for rasterising AIS data, and creating an image of it. First, the data is projected, essentially placing the locations in the data as dots on a canvas. Next, aggregates of specific variables are determined for reduction operators such as *count*, *sum* or *mean*. Potentially, transformations can be applied to the data, for example to shift between Coordinate Reference Systems (CRSs). The binned (aggregate) data is stored in a multi-dimensional array (we use *xarray* in Python). Creating an image that presents the variable aggregate(s), is done by assigning a colourmap to this data. The maps in Chapter 1 were created according this process, whereby Figure 1.2 used both colours and transparency to indicate traffic density, while Figure 1.3 used transparency to indicate traffic density, and colours were used to indicate vessel speed.

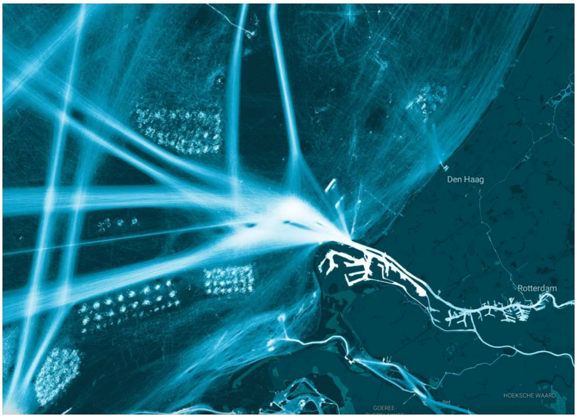
Dask is an open-source Python library for parallel and distributed computing (Rocklin, 2015). Dask creates a graph as a structured representation of task schedules with minimal incidental complexity, and distributes these tasks across multiple workers. Consequently, the computation time is drastically reduced, as the tasks can be executed in parallel, instead of sequentially. The rasterising process can be conducted in parallel, by partitioning the input data set (in this case AIS data in the top of the left flowchart in Figure 3.5). Considering the shape of the AIS data, consisting of a table whereby each row has the same columns in identical format, partitioning of this input data costs very little effort. Subsequently, the projecting of positions can be done in parallel, as well as the aggregation. Combining the outcomes of all partitions, finally, is an efficient step, as Dask can also do this through a parallel process. The resulting



(a) Visualisation by Emodnet



(b) Visualisation by MARIN (Duursma et al., 2019)



(c) Own visualisation

Figure 3.4: Vessel densities derived from historical AIS data for the North Sea coastal area (centered: port of Rotterdam)

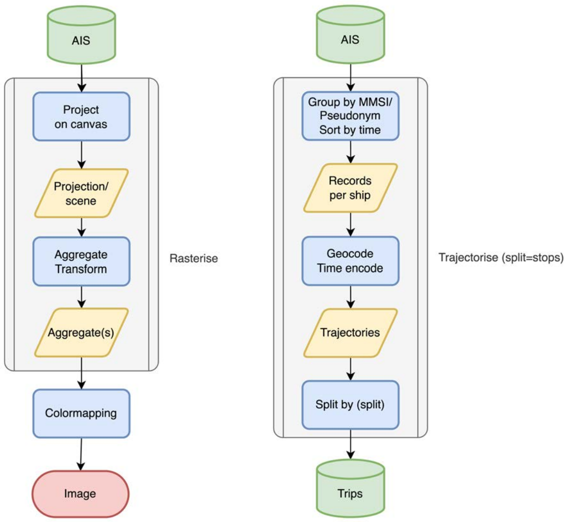


Figure 3.5: Flowchart for rasterising and trajectorising as part of the Scales perspective

multi-dimensional array should finally be turned into an image. To keep storage and file sizes manageable, we made use of tiling to create an image for a large area, that still entails the details.

Figure 3.6 and Figure 3.7 demonstrate the level of detail that can be obtained from zooming in on particular patterns that are observed at the high level. Figure 3.6a presents the coastal area near IJmuiden, where the sea locks are located that connect the North Sea to the channel into the Port of Amsterdam. The first zoom-in (Figure 3.6b) presents the area indicated with the top red rectangle, where dredging activities can be recognised. The sand is claimed at the location in the top-left corner, whereby the dredger moved slowly over longer stretches. The material is disposed at two locations near the coast, in the right-hand side of Figure 3.6b. Figure 3.6c presents several patterns at a high level of detail. On the left and top edges, the shipping lanes appear. Just South of the shipping lane, anchoring activities can be observed, whereby vessels slowly move at a fixed radius around their anchor, resulting in circular or moon-shaped patterns. The sharp, bright dots on the right-hand side indicate individual wind turbines, exposed by the installation and maintenance vessels mooring there. Finally, on the bottom, survey and other activities are performed to prepare for the installation of wind turbines in that area.

Figure 3.7 presents the coastal area at the North Sea and the Dutch Delta, South of the Port of Rotterdam. The large anchorage areas can be recognised in Figure 3.7a already, however, Figure 3.7b provides the rotation patterns of the vessels around their anchors in great detail. In Figure 3.7c, the high-density shipping patterns observed in Figure 3.7a can be recognised as fishing patterns (the bright, block-shaped patterns). Furthermore, in the bottom-right corner of Figure 3.7c, the 5 km-long *Zeelandbrug* creates a distinguishable pattern by its 54 pillars that vessels have to navigate around.

Parallel trajectory evaluation

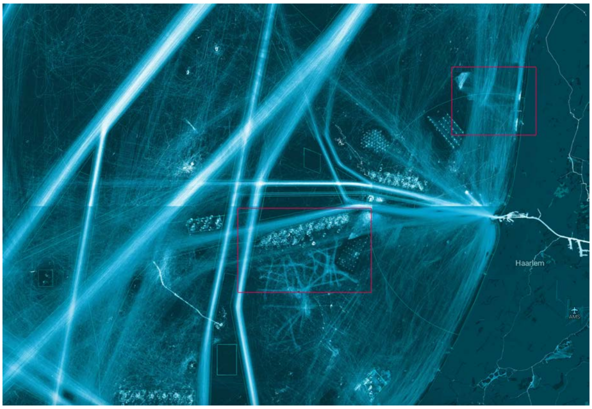
Besides rasterising, being at the basis for many visualisations, trajectorising is a process that can be executed through parallel computing, refer to Figure 3.5. Trajectorising gathers all data for each vessel, and stores them as trajectories. In this way, routes of individual vessels can be derived, instead of seeing uncorrelated positions on a map. After ensuring correct geo- and time encoding, the trajectories can be split into *trips* based on observation gaps or detected stops (for example, in a port). Python package *MovingPandas* was used for these analyses, whereby data was kept in a *Pandas* DataFrame form, making it suitable for parallel computing with Dask. The trip data are an important starting point for further analysis that considers individual vessel behaviour and external-factor interactions.

The temporal scope and resolution needs to be defined in correspondence with the behaviour that we want to detect. Depending on the application one might need to have information on the ships past weeks (e.g. weeks if one is interested in ships that might have picked up unwanted cargo from specific harbours). In this study, the focus is on a subset of behaviour (losing control, drifting) that should be observable in the order of 30 minutes. Therefore, for this study we focus on generating features over that timespan. The AIS data is split up into 30-minute trajectories following the procedure described in the right flowchart of Figure 3.5, whereby spatial point features with a time attribute, are first grouped by ship and subsequently by 30-minutes time window. Spatially, a coarse grid at OpenStreetMap (OSM) (Haklay and Weber, 2008) slippy map tile level 11, was defined as a basis to zoom, aggregate and filter.

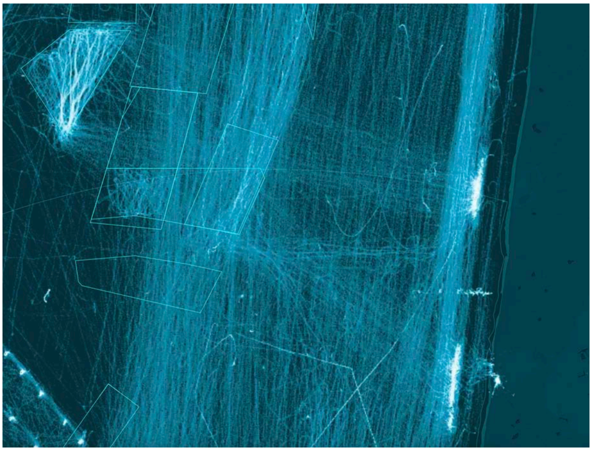
3.3.2. Conditions: connect with the context

For systems with moving agents, coupling the temporal and spatially varying environmental conditions with the varying positions of the agents, requires a certain resolution of the input data. Furthermore, being at a particular location can in itself already be related to behaviour; a car usually behaves differently at a parking lot than on a highway. These considerations are part of the Conditions perspective of the framework, which focuses on which external factors to be included in the analysis. If many factors are included, some of them may turn out to have limited or no influence. However, excluding potentially-influencing factors makes it difficult to adequately understand the behaviour or performance of agents, collectives, or the system as a whole. Hence, ideally, the relevant context should be identified upfront of the analysis, to avoid conducting (many) processing iterations.

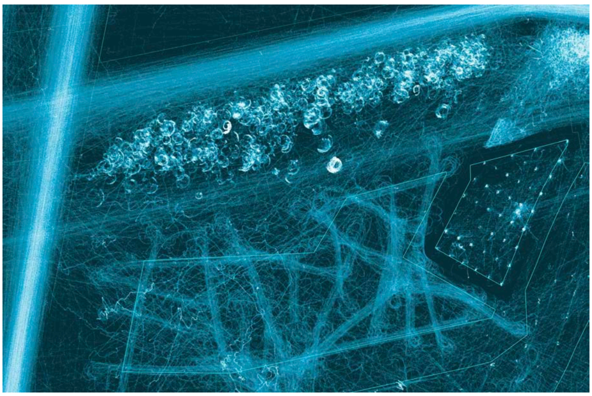
To identify different types of behaviour, different contextual knowledge is needed. For example, for the behaviour patterns distinguished by EMSA for ABM, the potentially relevant background knowledge to identify them is indicated in Table 3.1. For many types of patterns, location awareness is needed, e.g., it should be known whether the vessel is located in a port or at sea, and more specifically, inside or outside dedicated areas like anchorages or offshore wind parks. Other types require time-awareness, or nearest-vessel awareness, besides characteristics describing the vessel's behaviour (speed, course). Although of potential influence to the behaviour of a vessel, the environmental conditions do not explicitly come forward in the behaviour pattern categories (Figure 3.1 and Table 3.1).



(a) Nautical traffic at the North Sea near IJmuiden

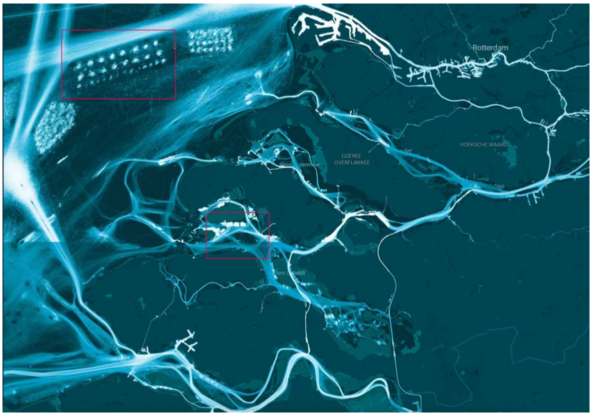


(b) Zoom-in on dredging activity North of IJmuiden

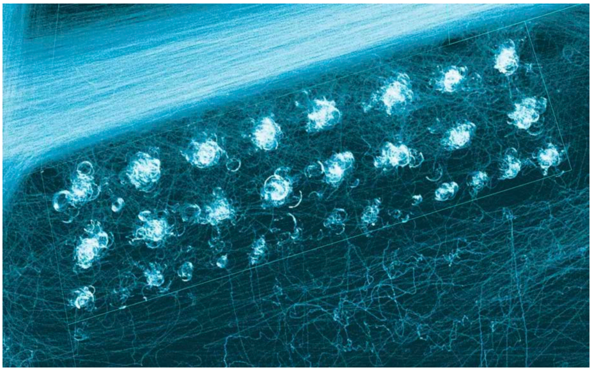


(c) Zoom-in on anchorage and wind park area

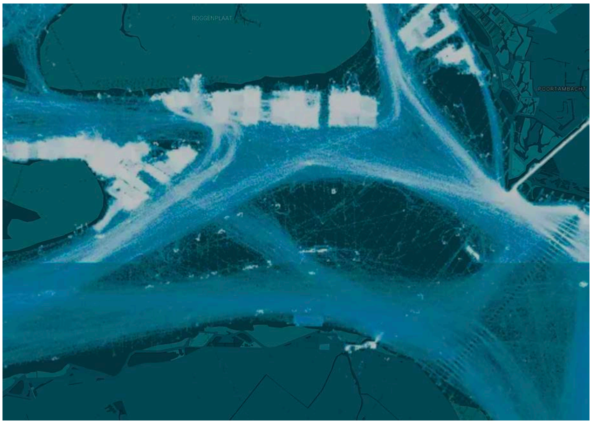
Figure 3.6: Vessel densities near IJmuiden and two zoom-ins indicated by the red rectangles in Figure 3.6a



(a) Nautical traffic at the North Sea and Dutch Delta



(b) Zoom-in on anchorage for Port of Rotterdam



(c) Zoom-in on fishing activities (top) and bridge crossings (bottom)

Figure 3.7: Vessel densities at the North Sea and Dutch Delta, and two zoom-ins indicated by the red rectangles in Figure 3.7a

Behaviour pattern	pos	sog	cog	time	other
Anchorage (outside port)	✓	✓			
At port at sea	✓	✓			
Drifting	✓	✓	✓		
At sea encounter	✓				✓
Spoofing position		✓	✓		
Not reporting		✓	✓	✓	
In/out area	✓				
Time of the day	✓			✓	
Sudden change of heading	✓		✓		
Sudden change of speed	✓	✓			
Heading to/off shore	✓		✓		
Distance to shore	✓				

Table 3.1: Required feature types for the ABM categories as defined by EMSA

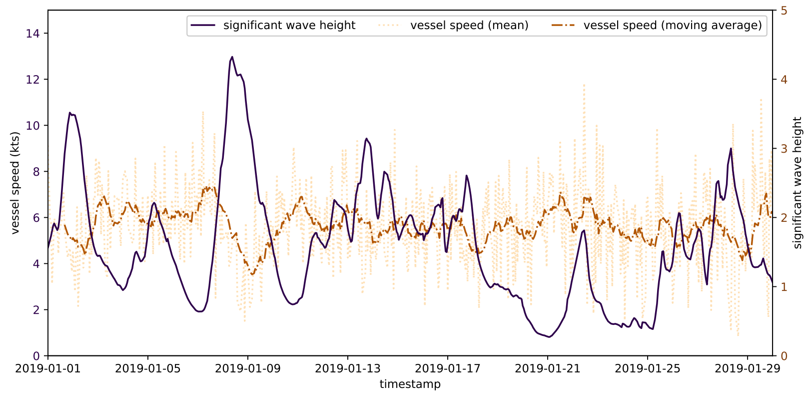


Figure 3.8: Hourly time traces of ERA-5 significant wave height and Northbound vessel speeds (mean and moving average) for the main shipping lane North of IJmuiden (North Sea) (van der Werff et al., 2024)

This is demonstrated by Figure 3.8, presenting the average vessel speed over time, of northbound vessels in the main shipping lane at the North Sea just North of IJ-muiden and Amsterdam, and the significant wave height over time at that location. The largest wave-height peak (around 09-01-2019) corresponds with a severe drop of the average vessel speeds; a relation that can be observed for smaller wave-height peaks as well. This indicates that vessels adjust (reduce) their speed in response to the environmental conditions (high waves) they encounter.

The selected data variables for the nautical safety monitoring case are presented in Table 3.2. Variables were selected based on the relevance and reliability of information. For example, AIS data provides information about the vessel type in various ways, whereby the 'vesseltype'-column is relevant for seagoing vessels, and the 'vesseltypeERI'-column is only relevant for inland waters, and hence, it is neglected in this analysis.

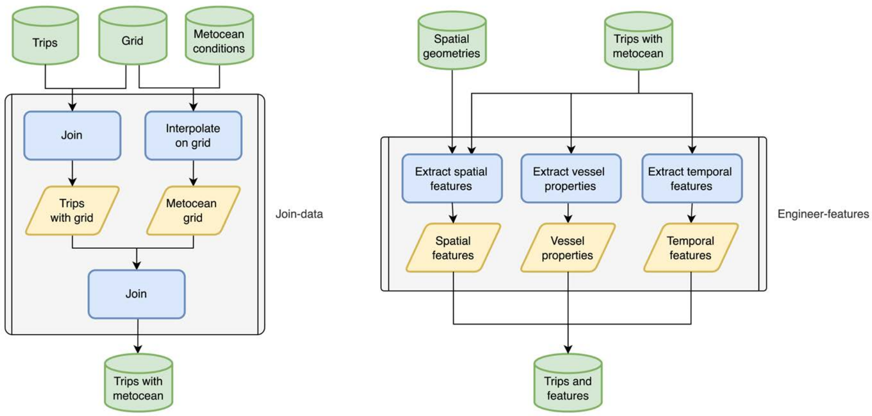


Figure 3.9: Flowchart for joining data sources and extracting features

Joining datasets

A concrete coupling needs to be made between components (agents) of the observed system and the identified external factors. This considers joining multiple data sources, and/or uniting information based on different grids or spatial and temporal sampling resolutions. The Conditions perspective entails the considerations for how to connect agents' behaviour to the contextual knowledge. The defined grid (at OSM tile level 11) was used as a spatial basis to join the datasets. On one hand, the grid was joined with the trajectorised AIS data, whereby the midpoint of each trajectory was used to determine its cell in the grid. On the other hand, the metocean data was spatially interpolated on the grid, resulting in variables describing the metocean conditions over time, at each grid location. This process is presented in the *Join-sources* function in the flowchart of Figure 3.9. Both data sets were joined on an hourly level, whereby the timestamp of the midpoint of each trajectory was rounded to the nearest hour, and based on their appointed grid cell.

Feature engineering

The characteristics for the conditions, as well as those describing the agent's behaviour, are extracted for each trip. Consequently, each trip is described by a set of attributes, or *features*. An overview of techniques to extract features from different time series data is presented in Table 3.3. Temporal reduction reduces a time series to features by integrating or differentiating. Aggregation consists of calculating the sum, mean, standard deviation, difference or minimum or maximum, etc. Spatial operations evaluate whether geometric boundaries were crossed during the trip, and space-time operations are temporal reductions or aggregations while a specific condition holds. Both require knowing the spatial features, e.g., the geometries that were crossed during the evaluated trip. Furthermore, (static) vessel properties were extracted.

The process is presented in the *Engineer-features* function in the flowchart of Figure 3.9. Using the operations described in Table 3.3, a total of 200 derived features were created. Hereby, the timeseries capabilities of the *tsfresh* (Christ et al., 2025)

Field	Description	Source
position	Point (longitude / latitude)	AIS
sog	Speed Over Ground [knots]	AIS
cog	Course Over Ground [degrees]	AIS
rot	Vessel rate of turn [degrees / s]	AIS
vestype	Vessel type category	AIS
vesdim	Vessel dimensions (length, width, draught)	AIS
currvel	Tidal sea water velocity (eastward, northward)	MATROOS
windvel	Wind velocity (eastward, northward)	ERA5
swh	Significant wave height	ERA5
wavedir	Wave direction (eastward, northward)	ERA5
anchorage	Anchorage areas	DGDR
northsea	Dutch part of the North Sea	DGDR
lanes	Shipping lanes	DGDR

Table 3.2: Overview of selected variables included in the analysis

Technique	Examples of resulting features
Temporal reduction	Speed, acceleration, angular velocity, wind speed increase
Aggregations (e.g. max, mean, sum, std)	Distance travelled, directional variation, maximum wave height
Spatial operations	Ship intersected anchorage, ship crossed shipping lane
Space-time operations	Duration in anchorage area, speed while crossing shipping lane

Table 3.3: Feature extraction techniques

library were used for temporal reduction and aggregations of the time-varying trajectory data. This resulted in vessel trajectory statistics features, summarising its dynamic properties. The spatial operations of the *Shapely* (Gillies et al., 2022) library were used to determine intersections between trajectories and spatial geometries, and intersections between trajectories and the boundaries of spatial geometries. This resulted in a binary feature for each spatial geometry type (i.e., TSS, approach area, anchorage area, or wind park) and the TSS-boundary crossing. Other, mostly static features, were derived manually, for example, vessel properties. A subset of these 200 features were selected for use in the further anomaly detection process, refer to Table 3.4.

Based on this set of features, much can already be determined based on rules. For example, based on a simple query, combining mean vessel speed and their presence inside and outside anchorage areas, can help highlighting vessels that behave out of the ordinary (because they were sailing slowly outside an anchorage area, or very fast inside an anchorage area). However, to identify some behaviour, and moreover, to reduce the number of false positives, rules tend to become complex, and potentially result in overfitting. The following section discusses how the set of over 200 features

Field	Technique	Features
vesdim	Static	[ratio length/beam]
sog	Aggregation	[mean, std, max, min, q-0.1, median, q-0.9, skewness]
rot	Aggregation	[mean, std, max, min, q-0.1, median, q-0.9, skewness]
lanes	Spatial op.	[int-anchor, int-approach, int-wind, cross-tss]
windvel	Static	[windvel-east, windvel-north]
currvel	Static	[currvel-east, currvel-north]
wavedir	Static	[wavedir-east, wavedir-north]
swh	Static	[swh]

Table 3.4: Selected features for anomaly detection

was used to detect anomalies in a data-driven way.

3.3.3. Behaviour: unfolding anomalies

An important step in unfolding behaviour is to come up with a wide set of variables and features that correspond to behaviour and reducing to a limited set of latent (unobserved) dimensions. The application of techniques that use latent dimensions have formed the fundament of psychometrics see Marsh et al., 2010, for example. These techniques have also become popular in detecting unusual and unwanted behaviour (e.g. Benchaji et al., 2021).

Dimension Reduction

For our application, a technique is required that not only reduces dimensionality but also groups similar behaviour together. Principal Component Analysis (PCA) would be a logical choice if our main focus was dimension reduction. Mapping similarities into a reduced dimension is commonly done using Multi-Dimensional Scaling. If these concepts are combined they are often referred to as manifold learning (see e.g. Han et al., 2022). For our purpose we will use the concept of Uniform Manifold Approximation and Projection (UMAP) (McInnes et al., 2020), which combines these concepts with a clustering approach. Herein, the *DensMAP* (Narayan et al., 2021) variant is used, to enable preserving the local density in order to also detect anomalous behaviour. Standardisation of the set of features, before the actual dimension reduction, was done by scaling to unit variance, even though not all features were Gaussian-distributed.

Applying this dimension-reduction technique on the features selected in Section 3.3.2 results in the so-called *embeddings*. Embeddings are the scores on the reduced dimensions which also contain information on the local similarities. Hence, it comprises a set of embedding parameters per trajectory (and corresponding set of features). For applying UMAP there are no set rules to determine the optimal number of dimensions (like the scree test in PCA (Cattell, 1966)), however, we have chosen for two-dimensional mapping, because it is a straightforward representation to interpret.

Clustering

Further understanding of the embedding can be achieved by clustering, whereby points in the embedding that are located close to each other, are grouped together. Consequently, similar vessel behaviour will become part of the same cluster. The *K-means*

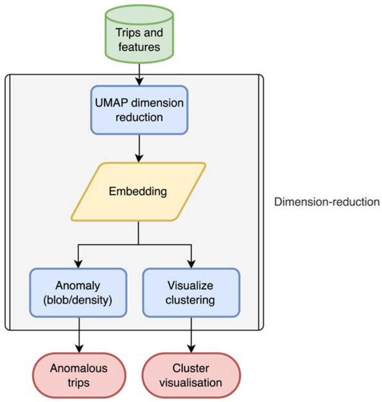


Figure 3.10: Flowchart for the anomaly-detection part of the process

clustering approach (Pedregosa et al., 2011) was applied, which separates the two-dimensional embedding array into *n* clusters of equal variance by minimising the inertia (or Within Cluster Sum of Squares (WCSS)) criterion (Bahmani et al., 2012). The number of clusters, known as the *k*-value, must be specified upfront, and was determined according to the Elbow method (Rao, 1971).

Anomaly Detection

Based on the defined behaviour in the form of embeddings, anomalous behaviour can be identified. We define three categories of anomalies: *global* anomalies, *within*-group anomalies, and *between*-group anomalies. The global anomalies can be detected on the original features (before dimension reduction). For example, the fastest sailed trajectory might be an anomaly, or, they can be detected using a multivariate set of features, for example, the trajectories that showed the highest variation in turns combined with the highest winds. Common "outlier detection" tools can be used to identify these anomalies. Refer to **??** and Figure 3.13 for an example of a global outlier, being a vessel that made a hard turn. In the within-group anomalies, also referred to as local anomalous, the behaviour is very similar to previously observed behaviour, but it deviates from the group. Local density estimates can be used to detect this kind of behaviour. Such an anomaly is presented in **??** and Figure 3.14, showing a mooring pattern, however, at a location just outside the anchoring area. The final category considers whether a group as a whole deviates from the rest of the population. Then, the entire group is anomalous if it is a rare occurrence. A combination of clustering and between-group feature statistics can be used to detect these anomalies, hence, outlier detection, but on a group level. An example is presented in **??** and **??**, showing multiple trajectories of one vessel that is sailing a remarkable pattern outside of the shipping lane.

In this study, a Local Outlier Factor (LOF) approach (Breunig et al., 2000) was used to determine which trajectories are anomalous, hence, focusing on within-group anomalies. This approach evaluates the local density of each point, being its distance to its

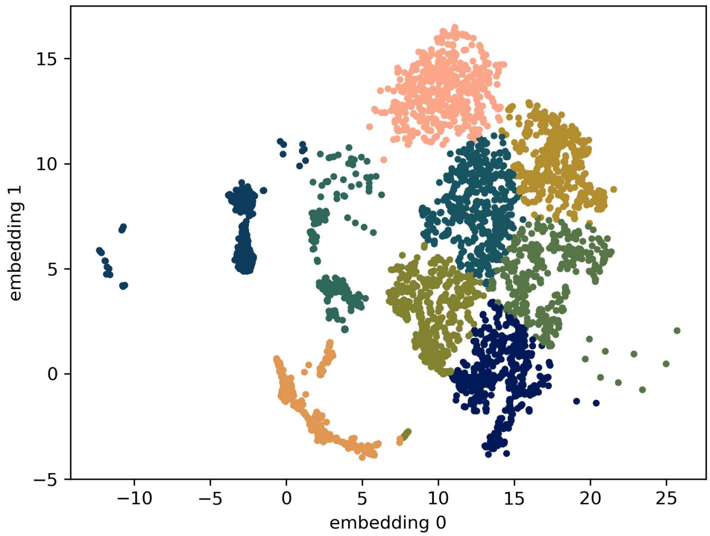


Figure 3.11: Generated embedding with colouring indicating distinguished clusters

k-nearest neighbours, with respect to the local density of its nearest neighbours. The number of considered neighbours was set to 20, and the contamination factor, determining the percentage of points identified as local outliers, was set to 1%. Based on the LOF-scores, the identified local outliers were ranked, with the most isolated points having the largest LOF-score.

The outcome of this approach is presented in Figure 3.16a and Figure 3.16b, whereby the red circles in the embedding indicate the 1% points ranked highest as local outliers. Figure 3.16b presents the vessel traffic heatmap with the trajectories corresponding to the identified anomalies in different colours. The question is, whether this approach is successful in truly detecting anomalous behaviour. This is demonstrated in Figure 3.17a and Figure 3.17b, where the points in the embeddings in the far left, are plotted in the right-hand side figure. All of these trips are made by the same vessel, being the Julietta D., drifting from its anchorage, crossing the wind park under construction.

3.3.4. Dependencies: labeling data

What has been presented so far, are the first steps towards machine-learning supported monitoring. Safety requires knowing sequential events indicated with time. A particular incident is not stand-alone, but it depends on events earlier in the chain. Actions of others may also have an effect on this course of events. These mutual dependencies become clear when examining recent shipping incidents. In the following section, the focus is on the investigations of the Julietta D. incident in 2022.

3

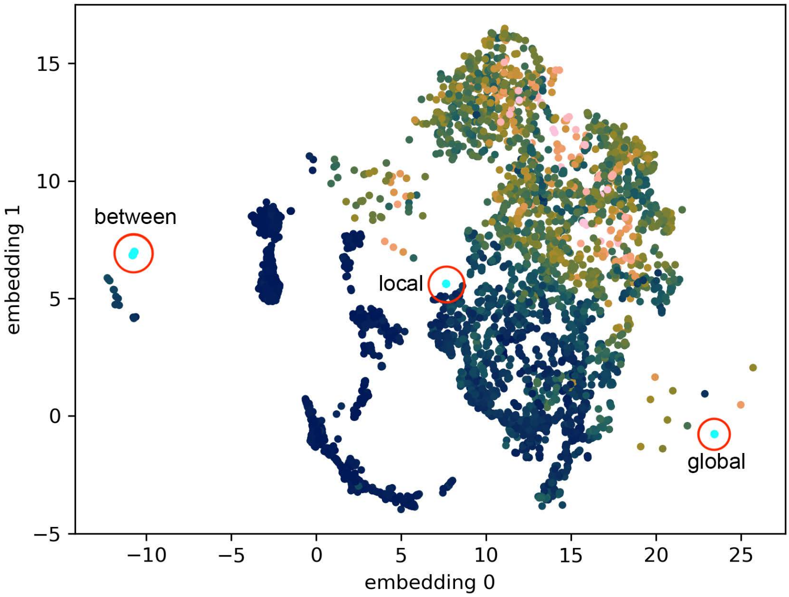


Figure 3.12: Generated embedding with examples of global, local, and between-group anomalous points

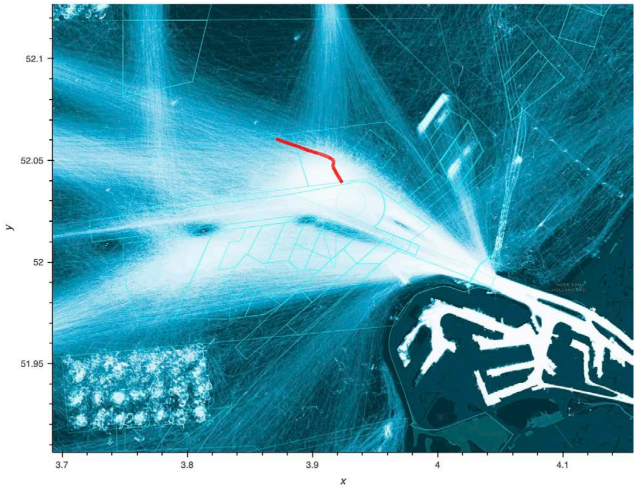


Figure 3.13: Global outlier: The trajectory corresponding to the anomalous cyan point indicated with “global” in the traffic density map of Figure 3.12

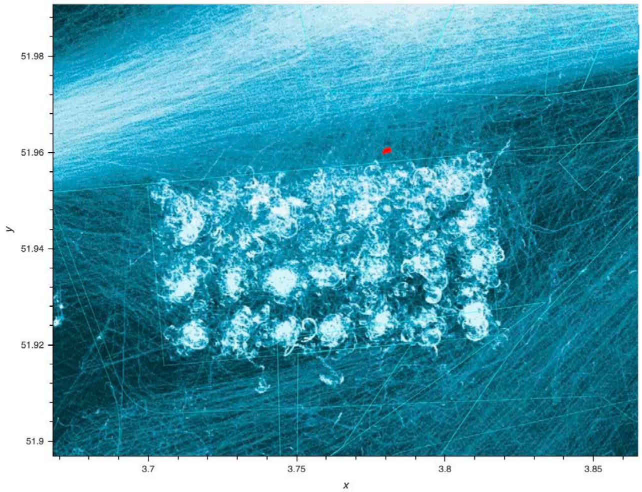


Figure 3.14: Local (within-group) outlier: The trajectory corresponding to the anomalous cyan point indicated with “local” in the traffic density map of Figure 3.12

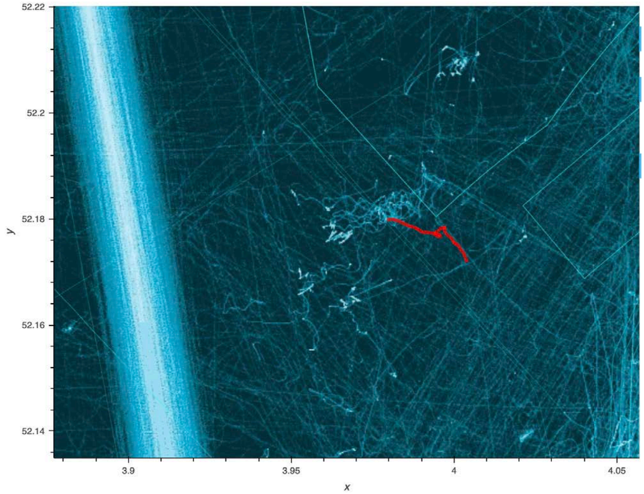
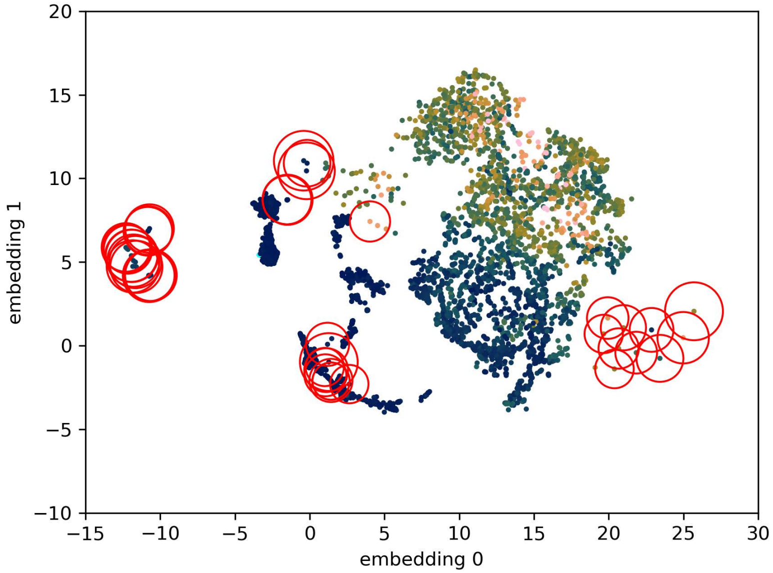
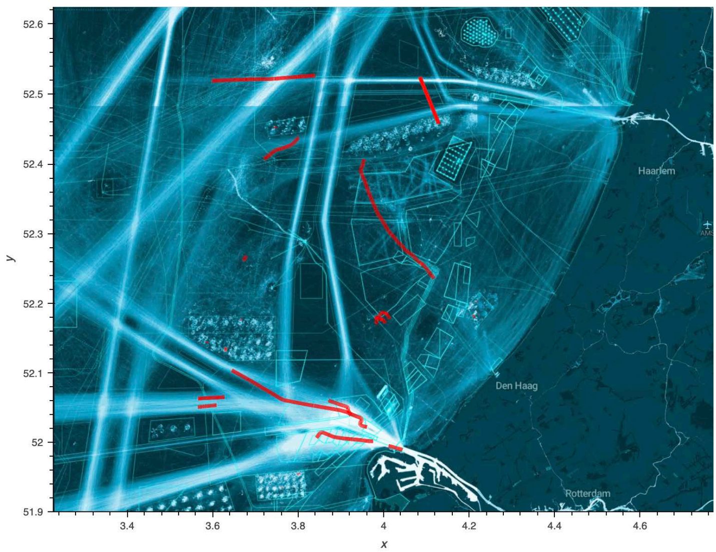


Figure 3.15: Between-group outliers: The trajectories corresponding to the anomalous cyan points indicated with “between” in the traffic density map of Figure 3.12

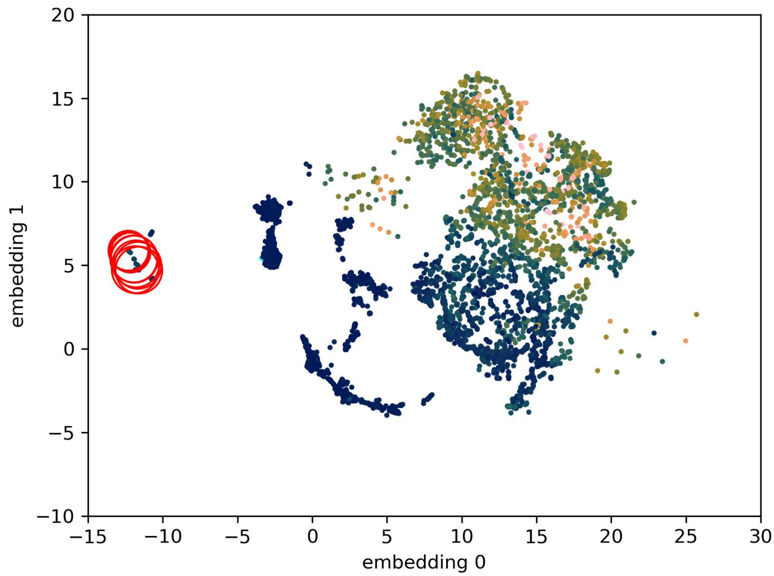


(a) Generated embedding with 1% local anomalous points indicated by red circles



(b) The trajectories corresponding to these points plotted on the vessel traffic heatmap

Figure 3.16: All points marked as anomalous in the embedding (a) and the corresponding trajectories on the map (b)



(a) Generated embedding with subset of local anomalous points corresponding to Julietta D.

(b) The trajectories corresponding to these points plotted on the vessel traffic heatmap

Figure 3.17: Subset of points marked as anomalous in the embedding (a) and the corresponding trajectories on the map (b), representing the Julietta D. track

3

Incident Cause Investigations

Several investigations have been performed to understand the sequence of events during the accident with Julietta D., with the aim of reducing the risk on similar incidents in the future. Given the flag state of the vessel, the primary investigation was conducted by the Maltese authorities (Marine Safety Investigation Unit, 2022). Given the location of the accident being in the Dutch Economic Zone, the Netherlands had a substantial interest in this case, and started a more general investigation into the high-intensity use of the Dutch North Sea coastal region (Umar et al., 2024).

Based on the Maltese investigation (Marine Safety Investigation Unit, 2022), Table 3.5 presents an overview of the events that have taken place during the incident, that was initiated by the vessel's mooring system failing while at anchorage offshore IJmuiden. Each event (row in the table) is characterised by different decisions that were taken, different states of the vessel, and different (environmental) conditions. Moreover, these states of events influence, or even trigger, the state of subsequent events. For example, the collision of Julietta D. with the Pechora Star caused hull damage, flooding the engine room, defecting the main engine, and posing the vessel Not Under Command (NUC). In its turn, had any of the states or conditions (locations of the vessels, condition of the mooring system, etc) be different, the collision between the vessels might have been avoided.

In their report (Marine Safety Investigation Unit, 2022), the investigators stated multiple scenarios in which other decisions or other vessel conditions may had resulted in a different (better) outcome. For example, the vessel's state of very lightly ballasted, resulted in a strongly comprised steering capability due to the large wind area and the rudder and propeller for a large part not being submerged. Moreover, it's rolling period was very short due to the high Metacentric Height (GM)-value corresponding to this loading condition. Deciding on taking in more ballast water might have resulted in a different chain of events, however, several arguments were raised of why the captain had decided against it. Furthermore, alternative scenarios were considered to heave-up the anchor and seek shelter or more manoeuvring space, as the Safety Management Manual (SMM) recommended against mooring during the foreseen heavy weather conditions. And even beyond on-board decision-making, alternate circumstantial conditions might had reduced the impact of the incident, whereby the investigators referred to the spatial layout of the anchorage providing no shelter for Northwesterly wind conditions, and to the consideration to place physical boundaries around offshore wind parks.

Opportunities with Labeled Data

Based on the Julietta D. investigation, we can conclude that to fully understand the root causes of an incident, requires having properly labeled data. Such data is presently unavailable. Registering incidents in databases such as the SOS-database (Rijkswaterstaat, 2024a) is a good start, however, not all incidents are reported (Vreugdenhil, 2013), and the incorporated information about the accident may be incomplete or incorrect (van Engelen, 2023). To achieve desired labeled data quality, would demand from the Coast Guard that they add a tag to every event in the chain, which is an impossible task in addition to their primary assignment.

Time	Event	Context
23-01 18:30	JD. arrives at anchorage	Decision: no additional ballast water Vessel: ballast condition, at anchor Conditions: Beaufort 3, Waves
30-01 12:30	JD. relocates in anchorage	Decision: more Northward for space Vessel: ballast condition, at anchor Conditions: Beaufort 6
31-01 03:00	JD. starts main engine	Decision: engine for heading control Vessel: heading control, at anchor Conditions: Beaufort 7, Waves 5.0-6.0 m
31-01 –:–	JD.'s mooring system fails	Decision: - Vessel: drifting, engine running Conditions: Beaufort 9, Waves > 6.0 m
31-01 10:28	JD.'s SOG reaches 3.0 kts	Decision: full engine speed and rudder Vessel: limited manoeuvrability Conditions: Beaufort 9, Waves > 6.0 m
31-01 10:30	JD.'s SOG reaches 5.5 kts	Decision: full engine speed and rudder Vessel: limited manoeuvrability Conditions: Beaufort 9, Waves > 6.0 m
31-01 10:43	JD. collides with PS	Decision: restart engine Vessel: damage, engine room flooding Conditions: Beaufort 9, Waves > 6.0 m
31-01 11:12	JD. stops engine	Decision: abandon ship, stop engine Vessel: drifting, NUC Conditions: Beaufort 9, Waves > 6.0 m
31-01 11:20	JD. collides with pile	Decision: Vessel: drifting, NUC Conditions: Beaufort 9, Waves > 6.0 m
31-01 11:30	JD. evacuation by helicopter	Decision: all crew evacuated Vessel: drifting, NUC, unmanned Conditions: Beaufort 9, Waves > 6.0 m
31-01 14:36	JD. collides with platform	Decision: - Vessel: drifting, NUC, unmanned Conditions: Beaufort 8, Waves 5.0-6.0 m
31-01 18:30	Sov. connects to JD.	Decision: - Vessel: limited towing control Conditions: Beaufort 6, Waves 5.0-6.0 m
01-02 01:00	Tug connects to JD.	Decision: not directly to port Vessel: controlled towing Conditions: Beaufort 4, Waves 4.0-5.0 m

Table 3.5: Events describing the incident with Julietta D. in January 2022, with abbreviations: JD.: Julietta D. (dry bulk vessel), PS: Pechora Star (tanker), Sov.: Sovereign (towing support vessel)

Eventually, when this data becomes available, the techniques presented above could be used to couple cause and effect, instead of just identifying a relation. Then, this same method would be used as a component in a supervised setting, whereby the dimensionality could be increased to improve the skill of the supervised model.

3.4. Chapter conclusions

Based on the four perspectives Scales, Conditions, Behaviour, and Dependencies, several challenges were identified on the road towards real-time monitoring support for vessel traffic monitoring operators. An integrated approach was proposed for the purpose of detecting anomalous vessel behaviour in the North Sea coastal area, thereby addressing each of these challenges. Using the challenge of scalability as one of the starting points, the overall approach was designed to be executed in a parallel setting, thereby improving the performance by multiple factors. This was achieved by trajectorising AIS-data and cutting them into trips of predefined duration, allowing parallel operations for each of the trips.

By applying dimension reduction before detecting anomalies incorporation of environmental, spatial, and vessel-specific factors was enabled, which was the second identified challenge. Although the relevance of incorporating these factors has been established, primarily because it reduces the number of false positives, an approach to achieve this in an integrated way, was lacking until now. The third challenge considered the interpretability of the outcomes.

In an operating setting like at Coast Guards, action upon a machine-identified anomaly can only be taken based on sufficient background information about the vessel, its behaviour, and its local circumstances. This is addressed by a maintained coupling between the two-dimensional embeddings and the trajectories including contextual information. By immediate visualisation of such a trajectory and presentation of its conditions, a faster decision can be taken to act, or not. The presented approach is extremely well-suited as a supporting tool, whereby an operator can opt for viewing the highest-ranked anomalous vessels, without needing to act on alarms.

The final challenge was about finding the root causes of incidents and understanding how to prevent them from happening (again). Based on investigations of the incident with drifting vessel Julietta D., it was concluded that root-cause finding requires availability of labeled data, in order to connect the chain of events in the right sequential order, revealing the correct interdependencies. In lack of such data for nautical traffic, this final challenge was not resolved in this study, however, it was possible to identify the added value of the presented overall approach, to detecting anomalies in the right context, once this labeled data becomes available.

4

Enhancing Transparent Allision Risk Assessments based on Comprehensive System Perspectives

I'm gone away in the morning
To see the world through different eyes
The further I get the closer I'll be
In every city and every sky

Gordon Groothedde, Bram Doreleijers, Marijn Van Der Meer, Illan Voshol, Jorrit Kleijnen, Robin Alexander Van Baaren

In this chapter, a real-world nautical case is considered, to determine the applicability of the framework introduced in Chapter 2. The case concerns the high-intensity use of the coastal waters of the Dutch North Sea. Several incidents have occurred, which emphasise the need for transparent risk analyses and identification of mitigation measures. Research question 4 is formulated as: ***How can generating an event table through the multi-perspective framework improve the assessment of allision risk-mitigating measures at the Dutch North Sea?*** Conceptualising the problem according to the four perspectives allows various views on the safety risks, providing a better understanding of the most important contributing factors, and the effectiveness of intervention measures. Moreover, it provides a basis for making the assumptions that are part of the analysis more transparent.

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4.1. Transparency of nautical safety risk analyses

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, 2020a; Minister of Infrastructure and Water Management, 2020b). 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, 2020a). 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 IMO (Marine Environment Protection Committee, 2018). The study concluded that “within realistic 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 Umar et al. (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 R. 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 Umar et al. (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 challenges by making use of an event table as introduced in Chapter 2: 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 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 chapter 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 assess their effectiveness by considering different operational strategies for Emergency Response Towing Vessels (ERTVs). This demonstrates 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.

4.2. Allision risk determination approach

4.2.1. Probability of an allision

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 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 unfavorable 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:

$$P_{\text{allision}} = P_{\text{geometric}} \cdot P_{\text{causation}} \tag{4.1}$$

$$P_{\text{geometry}} = P(L) \tag{4.1a}$$

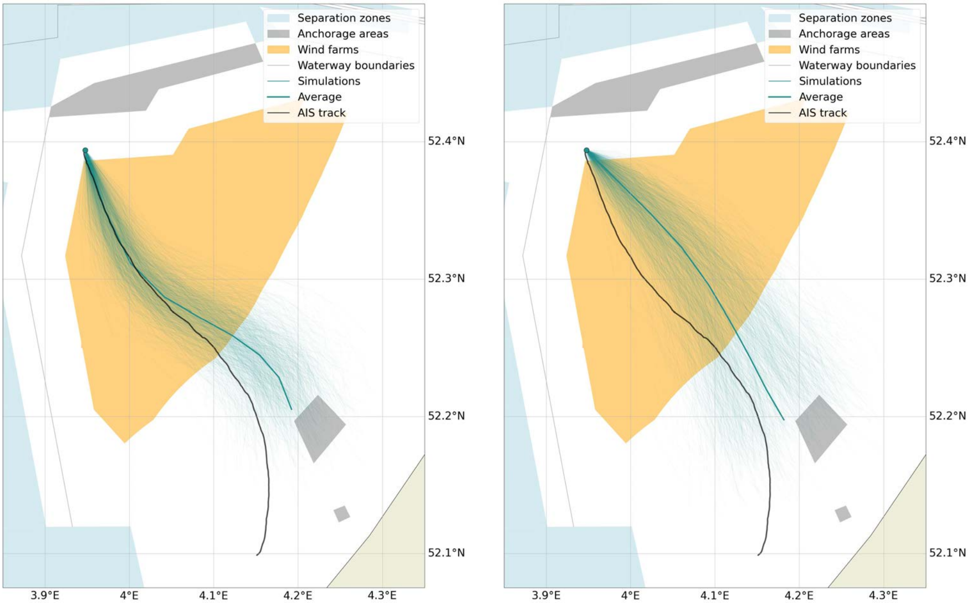
$$P_{\text{causation}} = P_{\text{adrift}} \cdot P_{\text{unfav direction}} \cdot P_{\text{no interv.}} \tag{4.1b}$$

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 Equation 4.1. Based on a comparative study between various drift trajectory models Eppenga identified the open-source *OpenDrift* application (Dagestad et al., 2018b) 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., 2018a). The *ShipDrift* module serves particularly for predicting the drift trajectories of vessels over 30 meters 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.

4.2.2. Simulation of vessel drift paths

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 Figure 4.1, 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 Figure 4.1a. 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.



(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

Figure 4.1: Simulated drift paths for Julietta D. with *OpenDrift* (Eppenga, 2024)

4.2.3. 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 Figure 4.2, 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 Figure 4.2 and a density map based on the AIS data for the evaluted area is presented in Figure 4.3. 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

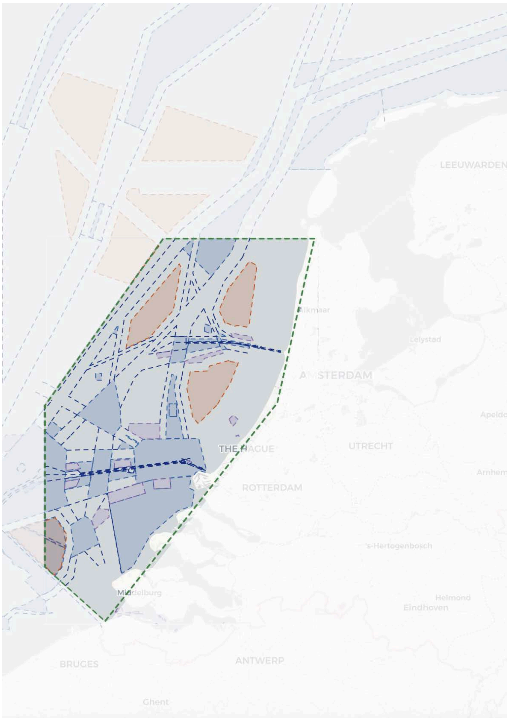


Figure 4.2: Traffic separation scheme (blue filled, with traffic lanes blue dotted), anchor areas (purple filled), and wind parks (red filled) in the considered area (green boundary dotted) at the Dutch North Sea, excluded area shaded.

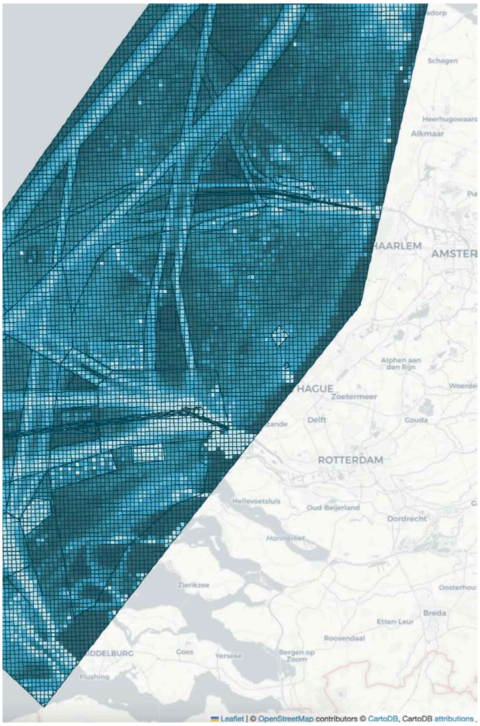


Figure 4.3: Considered area (non-shaded in Figure 4.2) with densities derived from AIS data projected on the constructed grid whereby the 1-by-1 km cells were divided at the boundaries of different utilisation areas.

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 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 hrs. Northerly and Easterly velocity components were used in the analysis.

Perspective	Requirement	
Scales - Spatial patterns of vessel-object allision risk levels and temporal trends	Fundamental components	Area of $\sim$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 and current speed, direction
	Influencing factors	Connect probabilities to corresponding background knowledge
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 - Couple drifting-time dependent course of events to external intervention measures	Initiations	Establish probability of timely arrival of ERTV and consequential residual risk

Table 4.1: Multi-perspective framework for defining analysis objectives and corresponding concept requirements for the analysis of vessel-object allision risks

4.3. Concept for multi-perspective evaluation of allision probabilities

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, the framework introduced in Chapter 2 was developed 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.

4.3.1. Conceptual model for multi-perspective probability evaluation

Table 2.1 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)).

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 4.1 how the framework is used to define the event table requirements for allision risks, distinguishing between the four perspectives:

4

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 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 achieve that the knowledge of a vessel crossing a wind park boundary is kept for hourly samples later in the drift track, even after exiting. 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 Figure 4.4. 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.

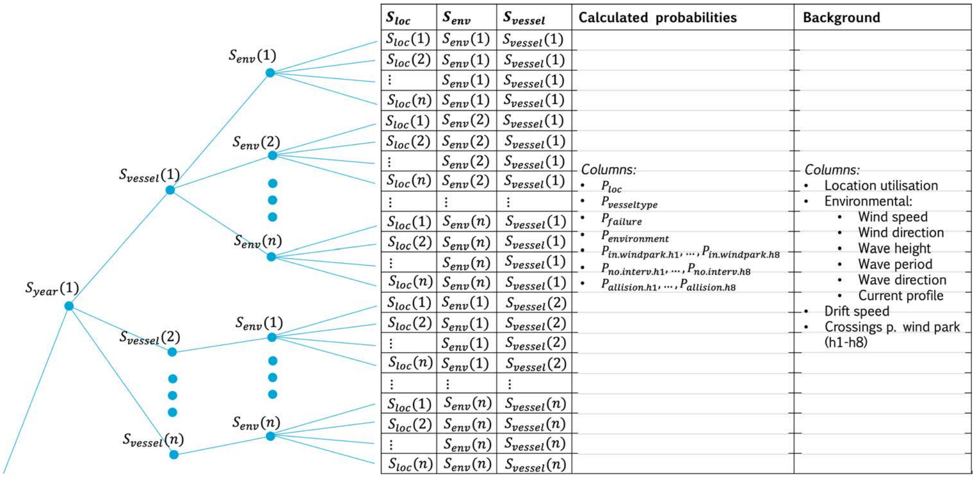


Figure 4.4: Construction of the event table by considering all unique scenarios.

Hence, the resulting event table is presented on the right-hand side of Figure 4.4. 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 4.3.2. Events with a zero probability of occurrence, that 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 Figure 4.4. Section 4.3.2 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 kilometer 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 Figure 4.3, whereby for each cell, the shipping density was determined based on AIS data, 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 4.2. 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 4.2. For the current profile, we considered 4 different starting times in a fixed, representative, tidal cycle, at 3 hour 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 4.3. 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.

Environmental parameter	Nr. of bins	Bin size	Description
Wind direction	8	45 deg	Bin medians equal compass directions (N, NE, E, SE, S, SW, W, NW)
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 and Current direction	4	3 hrs	Implemented through time traces with varying start times in tidal cycle

Table 4.2: Bins of environmental parameters to construct environmental scenarios

Cat	Bulk	Tanker	Container	Cruise
1	Handysize	Coastal	Early	1982-generation
	182x28x15 H:15	205x29x24 H:24	210x20x10 H:23	215x29x7 H:42
2	Panamax	Aframax	Panamax	1996-generation
	225x32x12 H:19.5	245x34x20 H:30	290x32x13 H:36	280x32x8 H:55
3	Capesize	Suezmax	Post-Panamax	2006-generation
	289x45x17 H:24	285x45x23 H:34	340x43x15 H:39	339x39x9 H:68
4		VLCC	VLCS	2009-generation
		330x55x28 H:42	397x56x16 H:47	360x47x9 H:72
5		ULCC	ULCS	
		415x63x35 H:52	400x61x16 H:65	

Table 4.3: 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

4.3.2. 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 4.3). 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 (Equation 4.1) multiplies P_{geometry} with $P_{\text{causation}}$, and our definition of an allision (Equation 4.2) 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 $P(E)$.

$$P_{\text{allision}} = P_{\text{event}} \cdot P_{\text{causation}} \tag{4.2}$$

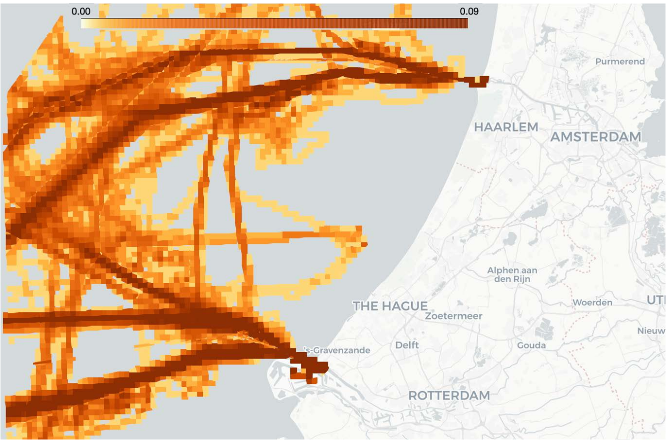
$$P_{\text{event}} = P(L) \cdot P(V) \cdot P(E) \tag{4.2a}$$

$$P_{\text{causation}} = P_{\text{adrift}} \cdot P_{\text{unfav direction}} \cdot P_{\text{no interv.}} \tag{4.2b}$$

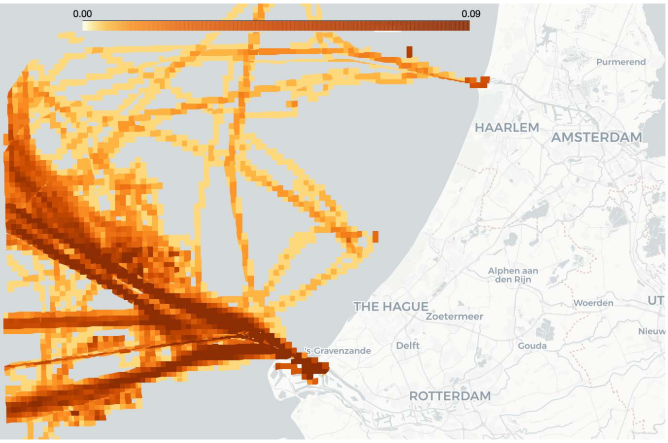
Each of these probabilities, as well as intermediate results to determine them, are stored in attribute columns of the event table.

Event probability

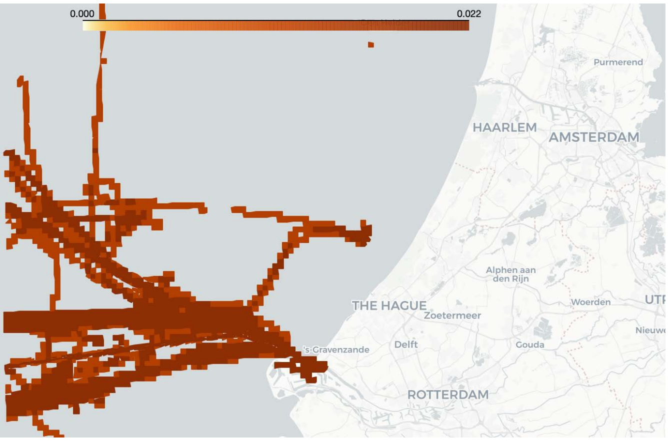
This section considers the approach for determining the event probability, as defined in Equation 4.2a. The location probability was determined by evaluating the number of vessel crossings for each cell in the grid, using AIS data. This was done by assigning each AIS sample to a cell in the grid. Samples 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



(a) Geometric probability of Aframax tanker

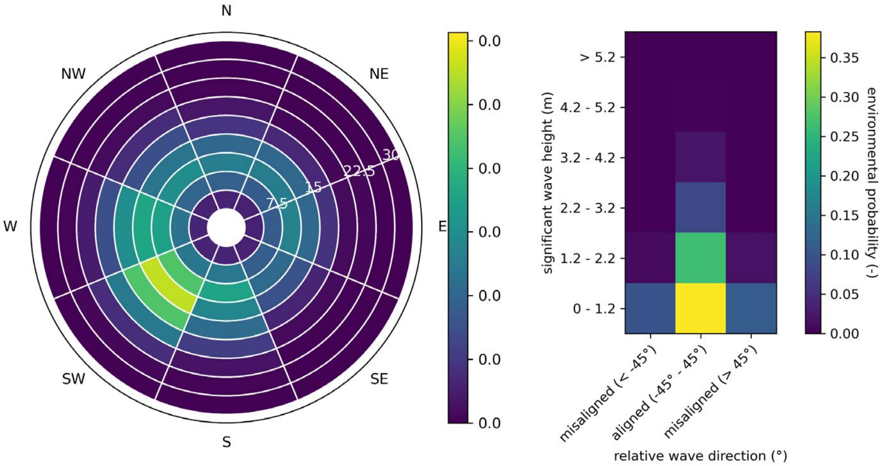


(b) Geometric probability of Suezmax tanker



(c) Geometric probability of a Very Large Crude Carrier (VLCC)

Figure 4.5: 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

Figure 4.6: Aggregated probability of occurrence for wind and wave conditions for the entire considered area

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. Figure 4.5 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. Figure 4.6 presents the probabilities of occurrence for all wind speed-direction combination (Figure 4.6a) and for all combinations of wave height and wave direction relative to the wind direction (Figure 4.6b). Note that both $P(V)$ and $P(E)$ are location specific.

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 Equation 4.3. The event-based approach facilitates more detailed conditional probability values based on expert opinions or

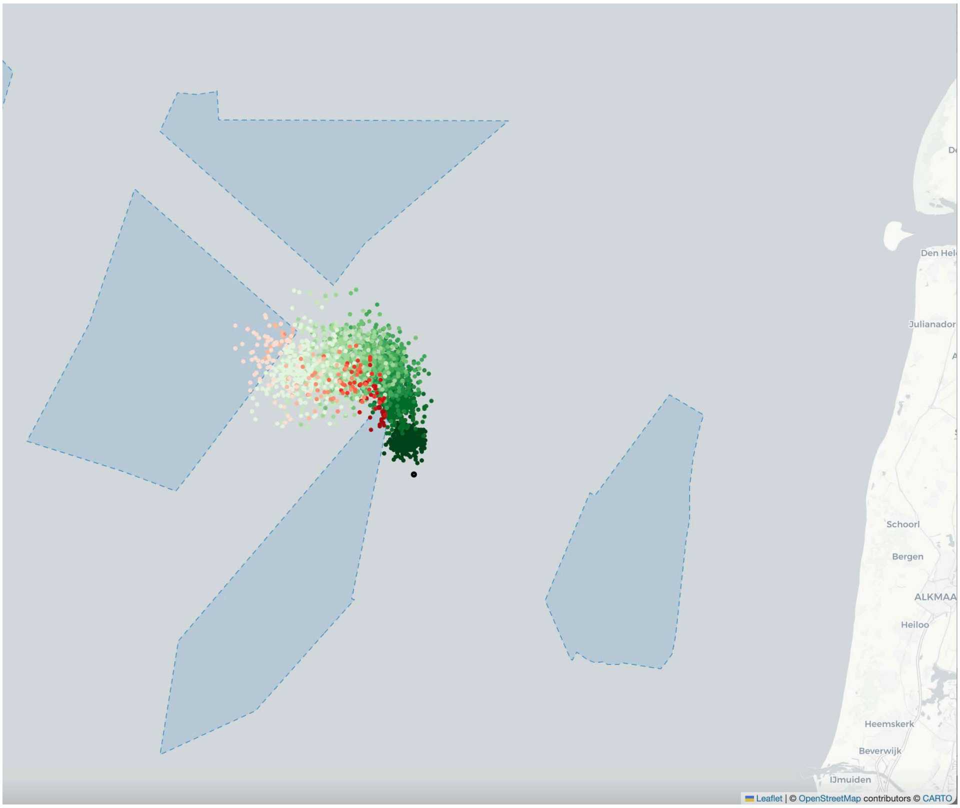


Figure 4.7: Evaluation of 300 drift paths (for one vessel type, and one environmental condition set) generated with *OpenDrift* for crossing of wind park. Red markers indicate drift paths that cross or have crossed a wind park, colour shades indicate drift time (darkest shades for short drift times)

extensive statistical data, if available.

$$P_{\text{adrift}} = \begin{cases} f(v_{\text{wind}}), & \text{if } L_{\text{utility}} = \text{“anchorage”} \\ 0.00025, & \text{otherwise} \end{cases} \tag{4.3}$$

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 hours, 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 Figure 4.7. 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.

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 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 Equation 4.4. 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.

$$P_{\text{no interv.}} = \begin{cases} 0, & \text{if } \dfrac{D_{\text{ERTV}}}{v_{\text{ERTV}}} \leq t_{\text{(drift in park)}} \\ 0, & \text{if } v_{\text{wind}} > 17.2 \text{ and large vessel type} \\ 1, & \text{otherwise} \end{cases} \tag{4.4}$$

4.4. Comprehensive multi-perspective view on allision probabilities

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 4.1. 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 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.

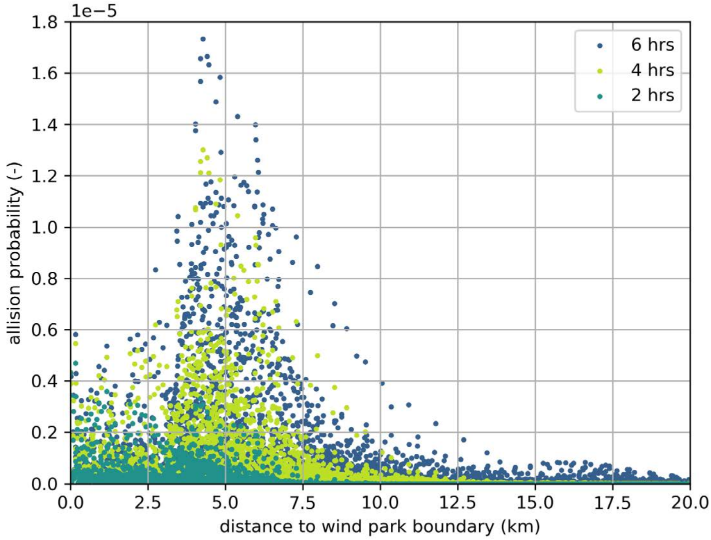


Figure 4.8: Allision probability for cell centroid distance to nearest wind park boundary

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.

Scales The first objective, from a Scales perspective, was to derive spatial patterns of the allision probabilities. Figure 4.9 presents three spatial "zoom levels" of this perspective, whereby Figure 4.9a indicates the allision probabilities after four hours, for all windparks in the entire area, for all vessel types. Figure 4.9b presents only the allision probabilities for one particular wind park, Hollandse Kust West, and Figure 4.9c 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 Figure 4.9c 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. Figure 4.9a 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

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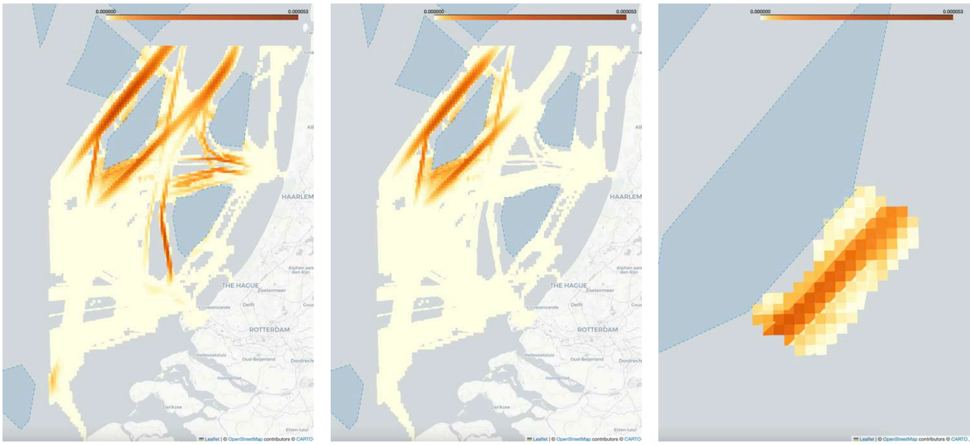


(a) Allision probabilities for all wind parks jointly (drift time 4 hours)

(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)

Figure 4.9: Zooming in at various spatial scales to evaluate allision probabilities

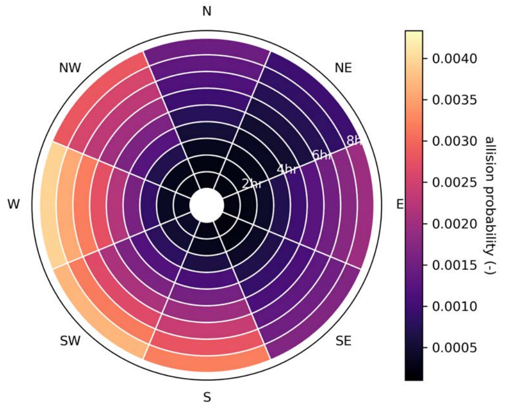
density reduces the allision probability. Furthermore, it can be observed that moving further away from the wind park decreases the allision probability. This is supported by Figure 4.8, showing the aggregated allision probability for each grid cell, based on its distance to the nearest wind park. The 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, however, by creating Figure 4.8 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 Figure 4.9, by extracting the contributing environmental conditions to these zoom levels. Figure 4.10 presents the contribution of the range of wind directions to the allision probability, for the same scopes as in Figure 4.9.

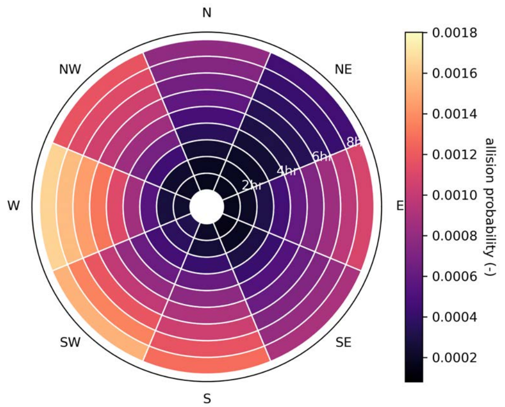
Based on Figure 4.6a it is known that the highest probability of occurrence is for wind speeds around 7 m/s (4 Beaufort) and wind directions coming from the Southwest range. Furthermore, the wind speeds from this direction are generally also higher than from other directions, which can be seen from the 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 (Figure 4.10a). The same is observed for the Hollandse Kust West wind park (Figure 4.10b), as the traffic lanes are situated all around this park. For the traffic lane area in Figure 4.10c, 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 Figure 4.11. Similar to the environmental conditions, we can investigate how different vessel types contribute to the allision probability. Comparing Figure 4.11a and Figure 4.11c 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 Figure 4.11b, which can be attributed to the large wind areas of container vessels.

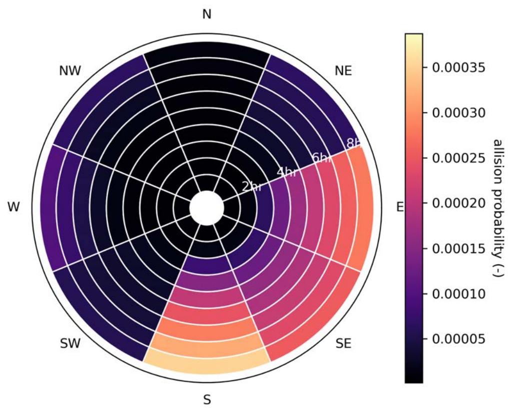
Dependencies As part of the Dependencies perspective, the aim was to evaluate the influence of external intervention measures on the allision probability. Figure 4.12 presents visualisations of extractions of the event table that can support assessing them, based on all incorporated vessel types, wherein the top row of maps present the allision probabilities without the intervention of an ERTV for 2, 3, and 4 hours of drifting, from left to right. We considered two ERTV strategies: the first entailed stationing ERTVs in Rotterdam and in Den Helder (refer to the middle row of maps for 2, 3, and 4 hours of drifting, from left to right), and the second entailed stationing ERTVs in IJmuiden and in Den Helder (refer to the bottom row for 2, 3, and 4 hours of drifting, from left to right). 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.



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

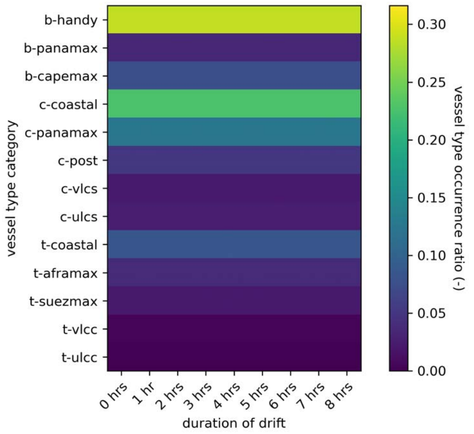


(b) Wind-park (Hollandse Kust West) specific allision probability contributions by wind direction, for 0 to 8 hours of drifting (from center outward)

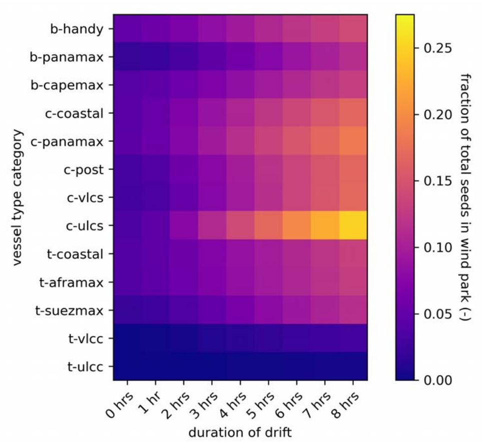


(c) Area (Southeast of Hollandse Kust West) specific allision probability contributions by wind direction, for 0 to 8 hours of drifting (from center outward)

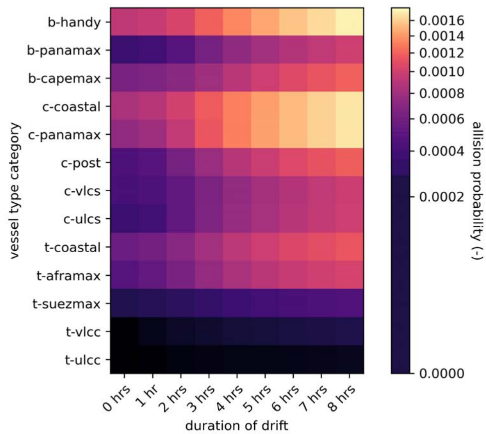
Figure 4.10: Various spatial scales for evaluating allision probabilities



(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

Figure 4.11: 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

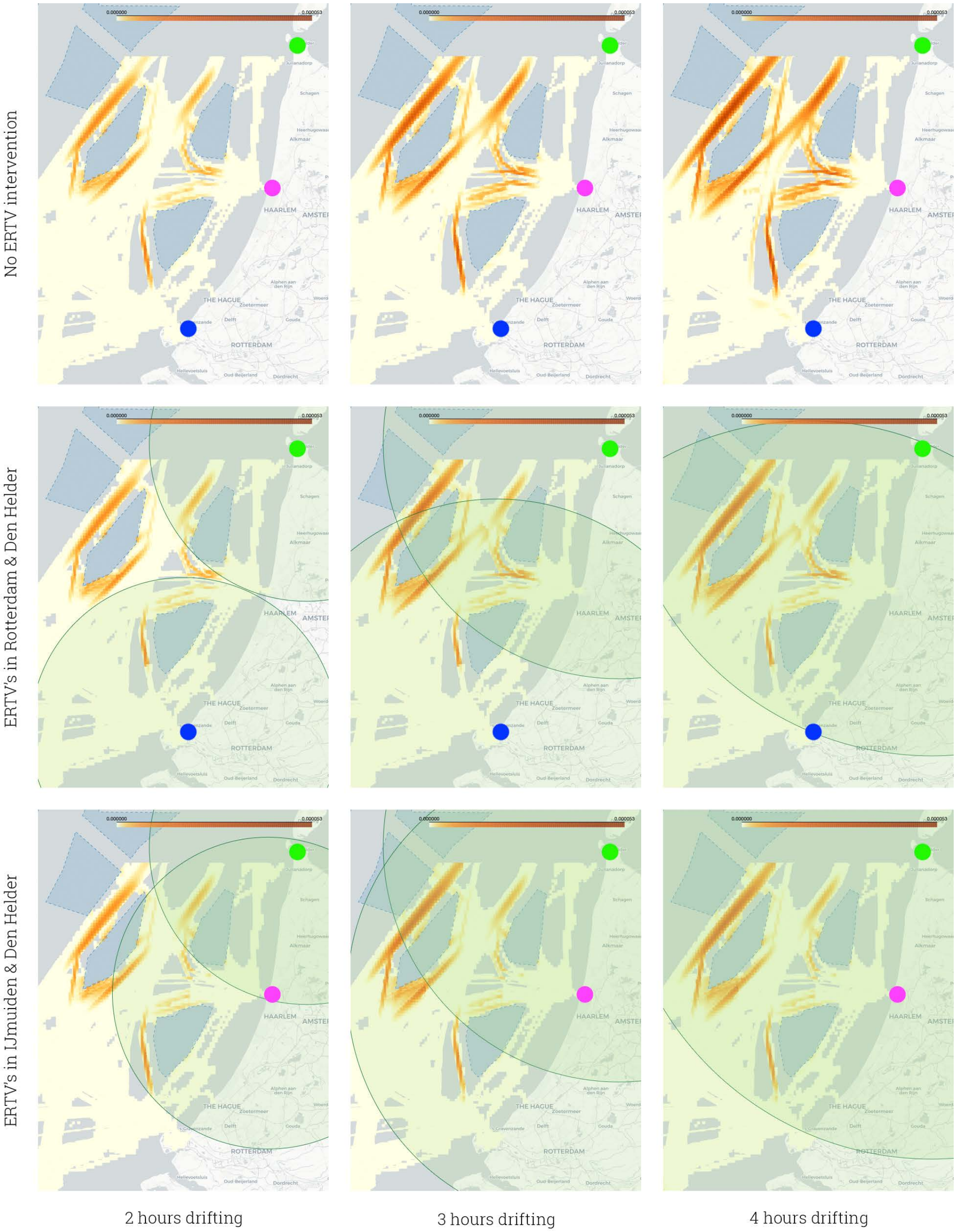


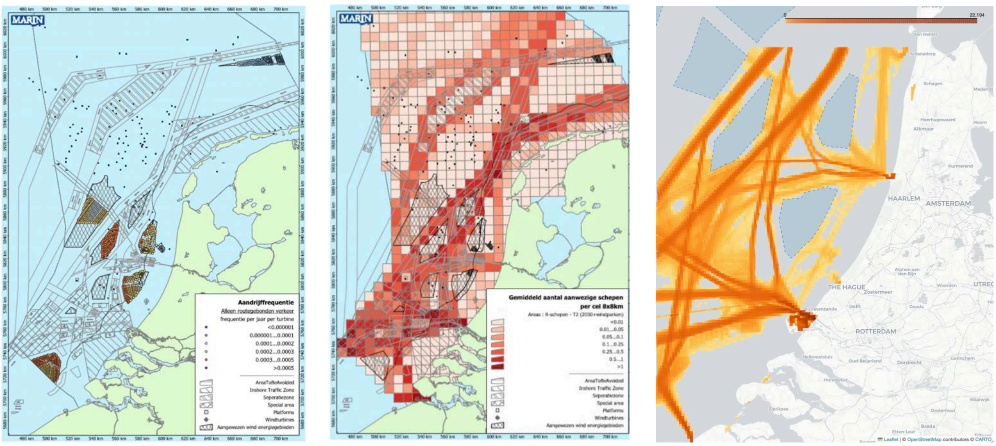
Figure 4.12: Allision probability after 2, 3, and 4 hours of drifting (varying with rows), and without (first column) and with ERTV intervention stationed at Den Helder and Rotterdam (second column), and with ERTV intervention stationed at Den Helder and IJmuiden (third column). Den Helder marked green, IJmuiden marked pink, Rotterdam marked blue.

4.5. Discussion of the multi-perspective allision probabilities

4.5.1. Comparison with allision probabilities in 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 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 Figure 4.13.

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 Figure 4.12. Second, comparing Figure 4.13b and Figure 4.13c, 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 Figure 4.9. This comparison demonstrates the improved flexibility to evaluate the risk-related outcomes from multiple perspectives and from various zoom levels.



(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 chapter

Figure 4.13: Comparison between various types of outputs related to allision risk analyses

4.5.2. Discussion of the approach to determine allision probabilities

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, like costs. 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 likely 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. Adding these consequences would greatly support the decision making for additional (expensive) risk-reduction measures, such as exploiting additional ERTV or increasing the buffer zones around wind parks.

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 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 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). The extent of uncertainties can be considered as comparable scenarios, as was done in this chapter. 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 4.4, 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.

4.6. Chapter conclusions

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.

5

Merged System Perspectives as the Key to Effective Inland Shipping Emission-Reduction Policy Design

Van de regen naar de zon
Van de hemel tot de grond
Van de regels naar de waarde
Voor de schepen, voor het water
Van de regen naar de zon en andersom

Dries Bijlsma, S. van Olst, Coen Witteveen & Typhoon

In this chapter, the applicability of the framework introduced in Chapter 2 is considered, using the real-world case of the emissions produced by the inland-shipping fleet. Policymakers in the maritime sector face the challenge to design and implement decarbonisation policies, while maintaining safe navigation. This requires an overall view of the emission patterns as well as detailed knowledge about the underlying causes. Research question 5 formulates this as: ***How can generating an event table through the multi-perspective framework improve the design of effective emission-reduction measures for the Dutch inland nautical system?*** By connecting observations in one perspective (for example, large-scale spatial patterns on a map) to supporting explanations based on another perspective (for example, water currents, vessel speeds or engine ages and their contributions to emissions), we provide an essential understanding of how the system works, and what the most effective improvement measures will be.

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5.1. Challenges in estimating shipping emissions

Worldwide, multiple economic sectors face ambitious emission reduction targets following the Paris Climate Agreement (United Nations / Framework Convention on Climate Change, 2015). The European Green Deal (European Commission, 2019) states that the inland shipping industry should contribute to these targets in two ways: as an alternative for less clean transport modes (emission reduction through modal shift) and by reducing the emissions of maritime transport itself (shipping emissions reduction). The modal-shift-related reduction follows from inland shipping being considered relatively environmentally friendly, with CO_2 emissions per ton-kilometres a factor of six lower than for road transport, and contributing to decongesting road networks (European Commission, 2019). Concerning the reduction of shipping-emissions, an ambition to decrease the shipping emissions with 50 % in 2050 was set by the IMO (Marine Environment Protection Committee, 2018). The Dutch inland shipping sector set its own ambitions to reduce greenhouse gas emissions by 55 % in 2030 and to become climate neutral in 2050 in the Dutch Inland Shipping Green Deal (2019). Policy makers now face the challenge to determine what (package of) measures they should implement to achieve the desired improvements.

We can identify three interrelated challenges when designing policies for the inland shipping sector. First, there is a large diversity of solutions that can be developed and implemented, ranging from highly targeted to very broad, with different effects locally and on the large scale. Second, the characteristics of fairways vary between corridors and even between fairway segments locally, resulting in different operating conditions for the inland vessels running on them. Third, the inland shipping sector constitutes for a large share a spot market, which makes vessel routing unpredictable. The first challenge can be considered based on Table 5.1, indicating regulatory, subsidy and operational examples of emission-reduction measures. Measures can be globally applicable, basically addressing all vessels, anywhere, regardless of their type or size, or targeted, considering specific vessels (Minister of Infrastructure and Water Management, 2022), specific areas (locks or port areas) or corridors (Zhao-Yu Song and Lee, 2023), or a combination of them (Port of Rotterdam, 2023). To understand which measures are effective, and at what scale and scope they should be implemented, requires evaluation that is detailed enough to consider the impact of local measures on the one hand, and covering a sufficiently large scope on the other.

The second challenge considers the large influence of environmental conditions

	Global	**Targeted**
Regulations	Fuel composition (EU regulations RED-III and ETS-2)	Local air quality requirements (municipalities, port authorities)
Subsidies	Engine renewal (compliant with latest emission standards)	Zero-emission shipping concepts, Alternative fuel corridors
Operational	Speed limits, water management implementation	Optimising lock operations, providing shore power

Table 5.1: Examples of various emission-reduction measure types (RED is the Renewable Energy Directive and ETS is the Emissions Trading System)

on the emissions, and their spatial and temporal variations. Luo et al. (2024) demonstrated the necessity of considering dynamic meteorological conditions in vessel sailing speed optimisation models, as opposed to static predictions. This importance also comes forward in literature on measurement campaigns executed at the banks of busy shipping routes like the Yangtze river (H. Jiang et al., 2021), the Rhine river (Kurtenbach et al., 2016; Eger et al., 2023; Krause et al., 2023) and the Waal river (Keuken et al., 2014). All studies emphasize the strictly limited applicability of the results to the measurement location, due to the large influence of environmental conditions on the measured emissions and their spatial variations. H. Jiang et al. (2021) compared AIS-based calculation with measurements and found large differences, that could partially be assigned to the effect of environmental conditions, which were not considered in the calculation model. Eger et al. (2023) conclude based on their data that vessels adjust their behavior according to the encountered current, whereby upstream sailing vessels use a slightly higher engine load setting and thereby have a slightly higher Speed Through Water (STW); the environmental conditions influence the emission levels directly as well as indirectly through the adapted behavior of the vessel. Keuken et al. (2014) furthermore conclude that one out of three vessels is a 'gross' polluter, implying that a focused targeting of the most polluting ships could be an effective way to reduce a large share of the emissions. Considering variations in vessel and operational characteristics as well as environmental conditions, PIANC-InCom-WG234 (2023) concluded that different corridors have different decarbonisation paths, calling for an approach that can consider the contributions of local influences to large-scale emission estimates.

Finally, the unpredictability of the inland vessels routing is a challenge because of the uncertainty it introduces when extrapolating case-study results to region-level or fleet-level conclusions. Life-cycle analyses have been made to derive potential emission reductions for alternative energy sources like methanol, Liquefied Natural Gas (LNG), hydrogen or batteries (Fan et al., 2021; Evers et al., 2023; Fan et al., 2023), or for scrubbers (Tan et al., 2022), and speed optimisation studies were conducted for various propulsion systems (Gao et al., 2017; Y. Zhang et al., 2023). Furthermore, energy supply solutions have been addressed for port areas (Ahamad et al., 2018) and for inland waters (M. Jiang et al., 2023). Many of these studies focused their analyses on one or a small number of representative ship-environment combinations, described by several case design parameters. Given that the operational profile of a vessel varies greatly, a feasible solution for a case defined by these specific parameters, might not be feasible in reality. For example, Tan et al. (2022) recommended integrating their approach in a shipping network, incorporating various ship sizes, and to "investigate the choice behaviors of ships". Šimenc (2016) concluded based on comparison of emission calculators that outcomes of various methods vary depending on different parameters that may be applicable at region level, to ship level, and even up to "waterway sections of a single transport operation by the same ship". Hence, the case studies should be evaluated in a broader context. To do this, a better understanding of the operational profiles of vessels, as well as the role of the encountered environmental conditions, is required.

Following the three challenges and what is required to tackle each of them, the goal in this article is to evaluate emissions considering the inter-connectivity between processes and influences at the detail level on one hand, and the emission patterns at the large-scale level. For maritime applications, first steps have been made by linking large-scale emission patterns derived based on AIS tracks, often presented in heat maps, to characteristics at the ship level. L. Goldsworthy and B. Goldsworthy (2015) indicated the contributions of distinguished operational modes to the total shipping emissions of sea-going vessels, and Jalkanen et al. (2012) made a breakdown of the total maritime shipping emissions into vessel size categories. As reflected by the three challenges, the inland shipping emissions, and the feasibility of potential policy measures, are strongly affected by spatially varying conditions. This drives the desire to further expand the possibilities to identify underlying details, from just ship-related details, to details that are related to location or time, or both. Commonly used system representations, or “schemes” for evaluating systems, do not accommodate investigating each of these details at once. Therefore, we apply a new, multi-perspective enabled scheme, called an “event table”, that facilitates deriving an overview of large-scale patterns, as well as inspecting the detailed contributions of processes related to vessel characteristics as well as environmental conditions in time and space.

We aim to demonstrate that these various perspectives and evaluation scales help identifying the most promising targeted emission reduction measures, like the examples stated in Table 5.1. We do this by considering the case study of vessel emissions on the Dutch inland water transport network. The presented results go beyond a presentation of the emission patterns, and dive deeper into their root causes, to finally help answering questions like: ”how can we design a strategy for fleet electrification?” and ”how much will engine replacement contribute to emission reduction in this system?” The applied scheme, presented in Section 5.3.1, facilitates joining multiple data sources and calculation approaches, that are first introduced in Section 5.2. The event table offers the flexibility to extract outcomes on multiple aspects related to the evaluation of inland shipping emissions and its causes, as demonstrated in Section 5.3.3. Finally, implications for policy design are discussed in Section 5.4.2.

5.2. Engineering approach to estimate emissions

5.2.1. Estimation of energy consumption and emissions

A comparison between multiple energy and emission estimate approaches for inland waters was made by PIANC-InCom-WG229 (2024), indicating that most approaches incorporate engine and ship specifications. In this study, we implement the Python-based OpenTNSim energy module approach (M. Jiang et al., 2022), because it was found to be the only approach taking into account corridor stretch specifications and local environmental conditions (PIANC-InCom-WG229, 2024). The theoretic foundation of this approach is briefly described in Appendix **??**. For an extensive description of the method, refer to Segers (2021) and van Koningsveld et al. (2023). A case study was performed by M. Jiang et al. (2023), underlining the importance of incorporating local conditions when designing corridor bunkering infrastructure for alternative fuels.

Figure 5.1 presents a schematic diagram of the emission calculation method. The applied module performs energy consumption and emission calculations for a time delta of one vessel at constant speed. Vessel resistance calculations are the starting point of the approach, as originally suggested by Holtrop and Mennen (1978), with corrections by Karpov as described by (Terwisga, 1989) and Zeng et al. (2019) to account for shallow water effects. Although detailed vessel shape and propulsion characteristics are required for this method, that are mostly unknown, the importance of including shallow water effects has been found to outweigh the details of the hull form (Hofman and Kozarski, 2000; Hekkenberg, 2013). Empirical formulations are included in the module to derive various hull-shape coefficients based on a fixed block coefficient of 0.85. The Specific Fuel Consumption (SFC) and emission factors were obtained based on the vessel's engine age and weight class following Ligterink et al. (2019). Emissions were derived based on the calculated instantaneous vessel break power. If, at low speeds, this power was found to be below 5% of the installed power, the engine was assumed to run stationary at this threshold value.

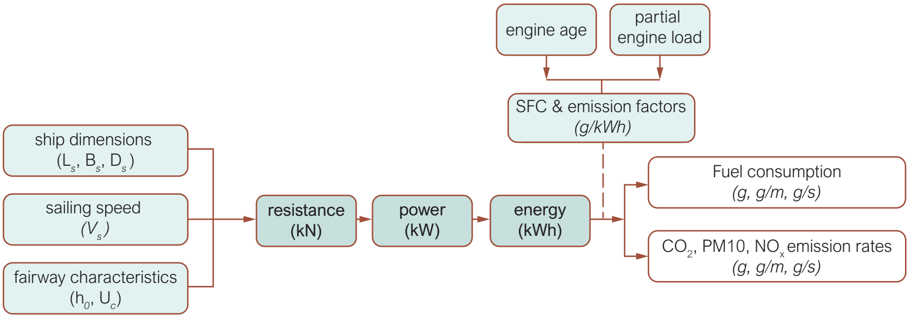


Figure 5.1: Methodology for estimating emissions for IWT vessels (image modified from Segers (2021), by TU Delft – Ports and Waterways is licenced under CC BY-NC-SA 4.0)

5.2.2. Data sources

The overview of utilised data sources is as follows:

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. Here we used anonymised AIS data, of the entire Dutch inland waterway network, for the months January, April and July of 2019 that were provided by Rijkswaterstaat, the executive agency of the Dutch Ministry of Infrastructure and Water Management, that collects this data for the Dutch territory. The data spans all Dutch inland waterways including the "IJsselmeer" and the Eastern and Western Scheldt, directing Antwerp. The AIS data was sorted by vessel identity, resulting in 33,229 vessel tracks, out of which 10,978 could be identified as commercial vessel based on the available vessel type and dimension information.

CEMT classification The use of anonymised AIS data shields information on the vessel's identity, which inhibits getting this information from other sources. We assumed installed engine power and weight classes from the Conférence Européenne des Minstres de Transports (CEMT) classification as published by Conférence Européenne des Ministres des Transports (1992), based on the main dimensions of the vessel.

Engine age distribution Engine ages, which are important for the emission estimates but generally not known at fleet level, were estimated from a Weibull distribution, derived by the Dutch Organization for Applied Scientific Research (TNO) from a sample among vessel owners, published by Ligterink et al. (2019).

FIS data Many waterway authorities nowadays share detailed properties of their waterway network through a so-called Fairway Information System (FIS). FIS data can be used to represent a waterway network as a graph of fairway segments (edges) that including properties of the individual fairway segments (width, depth, current). de Jong et al. (2021) published a topological fairway network derived from the Dutch FIS (Rijkswaterstaat, 2024b). It represents the Dutch fairway network by a graph in which edges represent fairway segments and nodes are located at the edge connections. Edge properties include among others linestrings of position coordinates indicating the topology, the segment length, and the limiting CEMT class which we used as a water depth indicator.

5.3. Concept for multi-perspective evaluation of shipping emissions

Our challenge is to derive inland shipping emission patterns, as well as to create an understanding of the underlying processes and factors causing them. Since these causes are related to the ship characteristics, the ship behaviour, and the ship's operating conditions that vary in time and space, we need a carefully designed concept that allows us to connect and investigate all of these facets. For this, the "event table" concept, as introduced in Chapter 2 is used, wherein essentially all data and calculations are gathered and organised.

5.3.1. Conceptual model for multi-perspective emission evaluation

The event table is inspired by the concepts of *moving features* and *event logs*. Moving features are a concept to keep track of a feature, viz. an object with properties, as a function of time and space (see Asahara et al., 2015). An event log, used in the field of process mining, is a collection of events, where each 'event' is defined by its 'case', indicating what process the event is part of, and its 'activity', being a well-defined step in the process (van der Aalst, 2012). The event table has adopted the ability to keep track of time and space from the moving features, and the principle of defining events from the event log. The table concept allows for filtering and aggregating operations on the data. The proposed data structure arises from the desire to evaluate the system from multiple perspectives, which is common for systemic approaches (Smyth and Checkland, 1976; Bunge, 1979; Lukyanenko et al., 2022).

The design of the event table is considered from four perspectives: scales, conditions, behaviour, dependencies, whereby each perspective is used to formulate objectives, and to translate this into design requirements for the event table, refer to Table 5.2. There are two types of columns in the event table: first, columns that jointly define a unique event (like the case and activity in the event log), and second, columns that provide additional information about each event, called attributes.

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 (meters, street/city/country level, etc.)
	Aggregation means	For deriving time aggregates (hours, days, weeks, months, etc.)
		For deriving spatial aggregates (street, river, area, state, etc.)
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 couple these 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 agents or processes 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)

Table 5.2: Pivoting perspectives used to define requirements to the framework

Table 5.3 presents the defined analysis goals for our inland shipping emissions case, together with the specified requirements for the data that we incorporate in the event table. We discuss the choices we made per perspective:

Scales We have to decide on how far we want to be able to zoom in, and how we can link the detail level and the higher levels up to the system level. AIS data is very fine grained, but has no means for aggregation in itself. Furthermore, environmental conditions are not available at this detail level, being in the order of several 10-100 meters. Therefore, we chose the FIS graph as a spatial hierarchic structure, placing the individual fairway segments in the entire Dutch fairway network. Consequently, the AIS data needs to be aggregated to the fairway-segment level as well. This is described in Section 5.3.2. Given that a vessel may cross a fairway segment in less than a minute, we want the time stamps to have at least an accuracy in the order of seconds.

Perspective	Requirement	
Scales - Spatial patterns of inland shipping emissions including hotspots	Fundamental components	Seconds Fairway segment
	Aggregation means	Fairway graph
Conditions - The influence of the environmental and physical conditions on the emissions	Fundamental components	Water depth, current speed Weather not considered
	Influencing factors	Intermediate calculation outcomes
Behaviour - Understand how vessel behaviour contributes to the emissions	Fundamental components	Vessel identity, trip and activity (sailing or pausing)
	Activity sequence	Time stamps
Dependencies - Not considered	Initiations	-

Table 5.3: Multi-perspective framework for defining analysis objectives and corresponding concept requirements for the analysis of inland shipping emissions

5

Conditions Identified influencing factors are the current speed and water depth. This drove the choice for the energy module calculation tool (refer to Section 5.2.1), and its input dependencies as presented in Figure 5.1. Fairway characteristics were extracted from the FIS (Rijkswaterstaat, 2024b), with exception of the water current, which was not available. Therefore, an estimate was made by determining the difference between the velocities of upstream and downstream travelling vessels for each time window of four hours. All intermediate results in the emission calculation process are required as attributes, to be able to understand how sub-processes contribute to the calculated emission total. Atmospheric conditions were not considered in this analysis.

Behaviour From the behaviour perspective we formulated the requirement that the emissions at the fairway levels, should also be traced back to a vessel identity, with specific characteristics. Ship dimensions were extracted from AIS. In case of incompleteness we turned to the CEMT classification. Vessels without any dimension data were excluded from analysis, as indicated in Section 5.2.2. Having anonymised AIS data obstructed coupling tracks with vessel identities and engine characteristics. Therefore, for each vessel an engine age was assigned by drawing from a Weibull distribution (Ligterink et al., 2019), which was derived based on a survey of inland-vessel ship owners. Furthermore, the installed power (used together with the instantaneous power to determine the partial engine load) and the weight class were assumed based on the CEMT class of the vessel. This class was also used to assume a draught in case of missing or unrealistic vessel draughts indicated in AIS data.

Moreover, we additionally want to distinguish between various trips of a vessel, to account for trip-specific vessel characteristics like draught and cargo. Lastly, we want to trace back what a vessel is actually doing. For this, we have limited information. The sailing Speed Over Ground (SOG) was extracted from AIS vessel trajectories. Using the tools available, we can only differentiate between vessels that are pausing (having a (near-)zero SOG) and vessels that are sailing (having a non-zero SOG).

Time stamps will be used to keep track of the sequence of activities that a vessel performs, i.e., the sequence of fairway segments that it travels. This allows for investigating individual or joint behaviour of vessels sailing particular routes with predefined origins and destinations.

Dependencies We decided not to consider the dependencies perspective. We do not have any data tying individual vessel actions to actions of other vessels, and we do not believe that the added value of retrieving this information through simulations would compensate for the required effort.

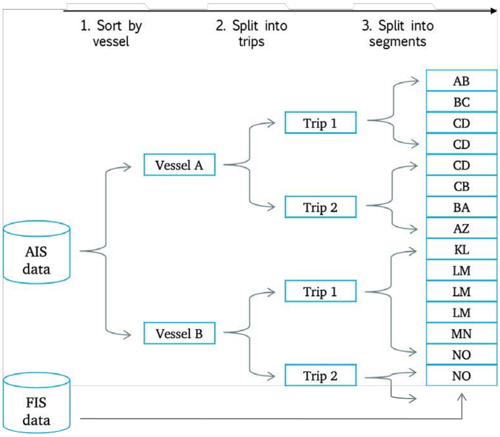
Based on the above decisions for each perspective, the event table was designed. A unique event is defined by considering all fundamental components, resulting in the following three variables: fairway segment, vessel trip, and time stamp. As all environmental conditions are connected to the fairway segment, this is considered a fundamental component. The same goes for all vessel characteristics, that are tied to one trip of one specific vessel. The time stamp ensures that two activities of a single vessel, taking place on a single fairway segment, can be distinguished, for example when a vessel is first pausing on the segment, and subsequently sails over that same segment. These three variables are the event-identifying columns in the table, jointly determining the number of events, hence, the length of the table. All other variables indicated are stored as attributes for each event.

Besides the possibilities, these considerations also reveal the limitations of the available set of materials. For example, the absence of reliable draught data forces making assumptions, although this is an important driver for the energy use of a vessel (M. Jiang et al., 2023). Furthermore, the anonymous AIS data prohibits coupling vessel tracks with other sources providing more accurate vessel characteristics, such as engine properties or transported cargo.

5.3.2. Event-based inland shipping emissions

To construct the event table, first, events were created representing the rows, and second, the emission calculation was performed to derive the emissions for each row in the table, whereby these were added to the table as attribute columns. Figure 5.2 schematically presents how the event table rows were constructed by creating events, being unique combinations of vessel trip, fairway segment, and time stamp. Herein, first, AIS data was sorted by vessel identity and filtered as described in Section 5.2.2. Second, the vessel tracks were split into trips using the Python package MovingPandas (version 0.14), based on a time difference in between two subsequent AIS samples in the vessel track exceeding 60 minutes, or by a cluster of multiple subsequent samples located within a diameter of less than 25 m exceeding 60 minutes. Figure 5.3a presents AIS vessel tracks, indicating different vessel trips by different colours.

Third, each trip was split into paths coinciding with a fairway segment as represented by an edge in the FIS graph. Figure 5.3b presents AIS vessel tracks, indicating



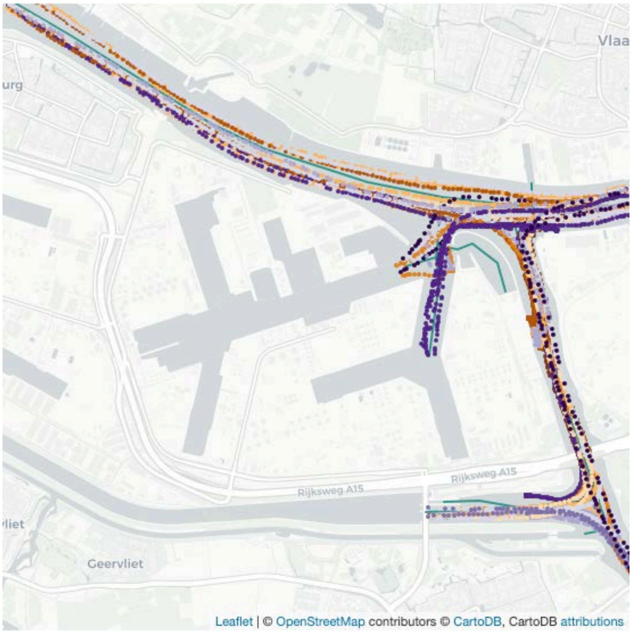
	Event ID			Attributes	
	Vessel Trip	Fairway segment	Instant	Path	...
1	Vessel A - Trip 1	AB	06:00		
2	Vessel A - Trip 1	BC	06:10		
3	Vessel A - Trip 1	CD	06:15		
4	Vessel A - Trip 1	CD	06:20		
5	Vessel A - Trip 2	CD	08:40		
6	Vessel A - Trip 2	CB	08:55		
7	Vessel A - Trip 2	BA	09:05		
8	Vessel A - Trip 2	AZ	09:10		
9	Vessel B - Trip 1	KL	13:30		
10	Vessel B - Trip 1	LM	13:40		
11	Vessel B - Trip 1	LM	13:45		
12	Vessel B - Trip 1	LM	14:10		
13	Vessel B - Trip 1	MN	14:15		
14	Vessel B - Trip 1	NO	14:25		
15	Vessel B - Trip 2	NO	15:30		

Figure 5.2: Creating the events as rows of the event table. Left: schematic process of breaking down vessel data into events. Right: simplified presentation of the resulting event table.

the fairway segment the vessel is located on by different colours. To do this, AIS samples were identified as a checkpoint following N. Andrienko and G. Andrienko (2013). Dijkstra routes were calculated between the closest nodes to the checkpoints in the FIS graph, and these were used to determine the closest edge to each of the samples in the AIS trip coordinates, thereby reducing computational effort as only a subset of the entire graph needed to be considered. Figure 5.2 presents a simplified event table, indicating each unique event to be a unique combination of vessel trip, fairway segment and time stamp. All events belonging to the same vessel trip have the same colour in Figure 5.3a, and all events located at the same fairway segment have the same colour in Figure 5.3b. The time stamp in the event table is equal to the time stamp of the first AIS sample in the path.

Starting from this event table layout, all required input for the emission calculation, as described in Section 5.2.1, could be added as attributes to the table columns: based on the vessel trip data, vessel characteristics could be added, based on the AIS path, the sailing speeds could be derived, and based on the combination of fairway segment and time stamp, instantaneous local conditions could be found. The only intermediate step before running the calculation schematised in Figure 5.1, was to derive the STW by correcting the SOGs for the speed of the current. Therefore, we estimated the water current speed on each fairway segment by aggregating the mean vessel SOGs over a time span of 12 hours, and comparing these velocities for upstream and downstream travelling vessels. For tidal waters like the Scheldt estuary, we used a time span of 2 hours and combined multiple fairway segments to have sufficient data. The current speeds were used to correct the vessel SOGs, resulting in vessel STW.

The emissions were calculated by applying the process in Figure 5.1 for each pair of AIS samples, resulting in arrays of resistance values, power values and emission values. Finally, the aggregates were calculated for each event. Input variables as well as intermediate calculation results were added to the attribute columns of the event



(a) AIS data categorised by sailing trip

(b) AIS data categorised by fairway segment

Figure 5.3: AIS data categorisations for a small number of fairway segments in the Port of Rotterdam

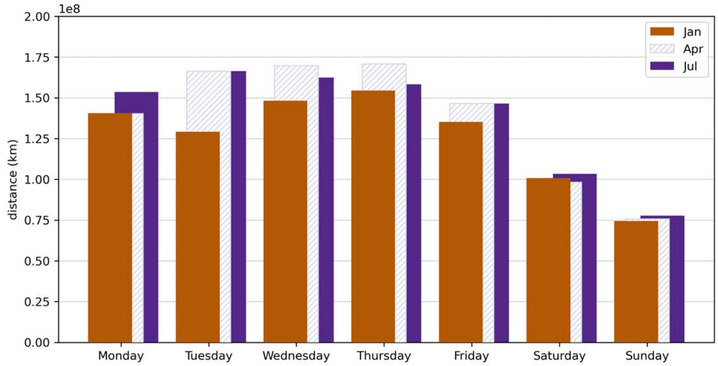


Figure 5.4: Sailed distances of total fleet in the Netherlands by weekday, monthly means for January, April and July 2019.

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table. Emissions were determined for each event, regardless of the potential idle time. By filtering on the duration and mean speed of the events, an assumed cutoff time for engine shutdown could be applied. All data processing was conducted using Microsoft Planetary Computer (Microsoft Open Source et al., 2022). Thereby, computation times were reduced from several days, to several hours. After all processing, we obtained an event table consisting of over 10,1 million rows and 52 columns.

5.3.3. Comprehensive multi-perspective view on shipping emissions

This section shows how the event table constructed in Section 5.3.2 can be used to analyse shipping emission patterns and connect these patterns with the underlying mechanisms. We present a couple of results from the various pivoting perspectives that were included in the event table design: viz. scales, conditions and behaviour.

Scales Looking at the Dutch inland-vessel emissions from the scales perspective, is the most straightforward way to connect system-level patterns to contributions of individual vessels. The key is to zoom out and zoom in into space and time. Figure 5.4 presents the means of the total sailed distance by weekday, presented for the three evaluated months separately. It shows a similar distribution of shipping activities in April and July and a deviating distance for January. The cause is found in New Year's Day (a public holiday on January 1st), falling on a Tuesday. The sailed distance was only 25% of the distance normally sailed on Tuesdays. To a limited extent, this was visible for the other days in that first week of the year. The same trends were observed for the emissions.

Figure 5.5 and Figure 5.6 show the distribution of the total shipping emissions over the fairway network, using colour and line thickness to indicate the emission levels, for CO_2 and PM_{10}. The emissions are presented in grams per kilometre to enable comparison between fairway segments of varying lengths. The overview allows us to identify hotspots and zoom in to investigate the root causes of these hotspots. The routes that connect Rotterdam, Antwerp and Duisburg can be identified as parts of the network that have the highest emissions. Additionally, a number of hotspots can be recognised in and near ports and locks, and at junctions. The hotspots were further investigated by zooming in on the fairway segments contributing most to the CO_2 emissions per travelled kilometre (see Figure 5.5). Besides the emissions, other characteristics can be evaluated, like the number of vessel passages, or the local conditions at that fairway segment.

Conditions Using the conditions perspective, we delved into the influencing factors of the emissions, by addressing two items. First, we considered how environmental conditions affect the shipping emissions, being one of our primary objectives. Second, we investigated the most important contributing factors to hotspots and how much influence they have in the total system. For the first item, we assessed the influence of the current speed and the water depth on the shipping emissions. Figure 5.7 presents the emissions per distance unit for sections on which currents were present (large rivers). It shows that sailing against the current has a drastic impact on the emissions, almost quadrupling them compared to a near-zero current, while sailing with the current shows to have only limited effect of 10% at most.

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Figure 5.9 presents emissions breakdowns for various parameters, in the appearance of hotspots A and C (river Waal in the left column and Volkerak locks in the middle column, respectively) and for the system as a whole (all Dutch fairways in the right column). Each figure indicates the sailed distance (purple, striped) and the emitted CO_2 mass (brown) per category.

Figure 5.9 presents the fleet types composition in the top row and the engine age of the vessels in the bottom row. For the vessel types, a similar pattern can be seen for both the two hotspots and the total system. The largest vessel class (V) covers the largest distance, but it has a relatively much higher contribution to the emissions. For the second largest class (IV) the share of the total CO_2 emissions is approximately equal to the share of the travelled distance, and the smallest classes emit much less CO_2 compared to the distance they travel. This result can be explained by the fact that larger vessels have a larger resistance to overcome, resulting in a higher energy use and higher emissions. Of course, it is noted that the cargo capacity of class V vessels is up to twice that of class IV vessels (Koedijk, 2020).

Categorising into engine age classes (middle row in Figure 5.9) shows that the distribution of engine ages is the same for the vessels at both hotspots and when considering all vessels in the system. Furthermore, the contributions of sailed distance and emissions indicate that vessels with modern engines only emit slightly less CO_2 per sailed kilometre than those with old engines. For the PM_{10} emissions, this distribution is very different, as indicated in Figure 5.8, where new engines contribute only a fraction of the total PM_{10} emissions, compared to the distance they covered.

Figure 5.5: Map of the Netherlands indicating CO_2 emission levels caused by inland shipping, and the most important hotspots

Figure 5.6: Map of the Netherlands indicating PM_{10} emission levels caused by inland shipping and the most important hotspots

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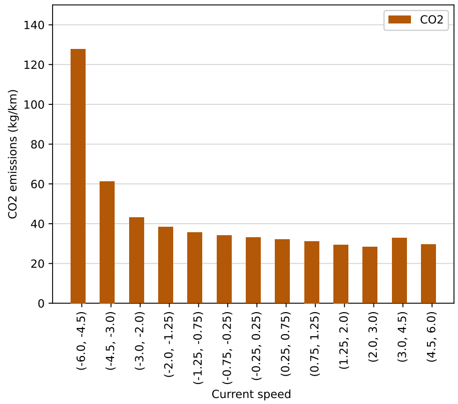

Figure 5.7: The effect of current on the CO_2 emissions per travelled distance unit

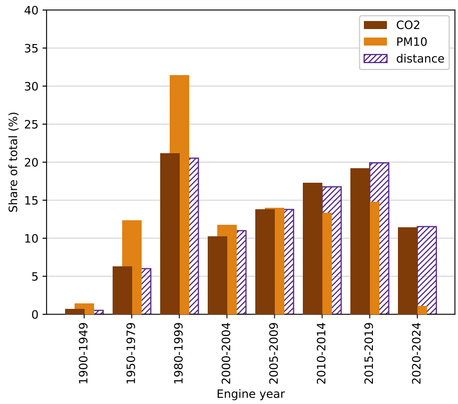

Figure 5.8: The contributions of various engine age classes on the total CO_2- and PM_{10} emissions

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To understand the uncertainty introduced by assigning engine ages to vessels based on the Weibull distribution (Ligterink et al., 2019), we evaluated the emissions for multiple realisations of engine ages for the fleet. It was found that the sum of the emissions in the system varied less than 0.3% for CO_2, and 3.4% for PM_{10} with larger variations locally.

Behaviour The behaviour perspective can answer questions related to sailing profiles of vessels and the consequences of their behaviour the produced emissions, under given environmental conditions. In the bottom row of Figure 5.9, we categorised into partial engine load, being an indicator for the sailing speed, whereby 10 engine-setting bins were used ranging from 10% (stationary) to 100% (full power). On one hand, at the river Waal hotspot, on a continuing shipping route, the emissions arise due to busy traffic at moderate and high sailing speeds (bottom left in Figure 5.9). On the other hand, for fairway segments near busy locks and ports, the emissions arise due to traffic slowing down, manoeuvring, and idling (bottom middle in Figure 5.9). How much both of these mechanisms influence the emissions in the total system, becomes clear from the bottom right graph in Figure 5.9. For high engine powers, the share of emissions is slightly larger than the share of sailed distance. However, about one third of the emissions is caused by vessels running idle (power in lowest category), while only 11% of the distance is covered using this engine setting.

Sailing at low partial engine loads is inefficient in terms of fuel use and emission production (Ligterink et al., 2019). To better understand how the emissions arise in the lowest engine-setting category, a further breakdown was made in Figure 5.10. The top chart presents the breakdown of the total CO_2 shipping emissions into the ten engine-setting categories. The middle chart indicates the share of the emissions in the lowest engine-setting category caused by sailing, and the share caused by stationary vessels. It shows that only 15% of the emis-

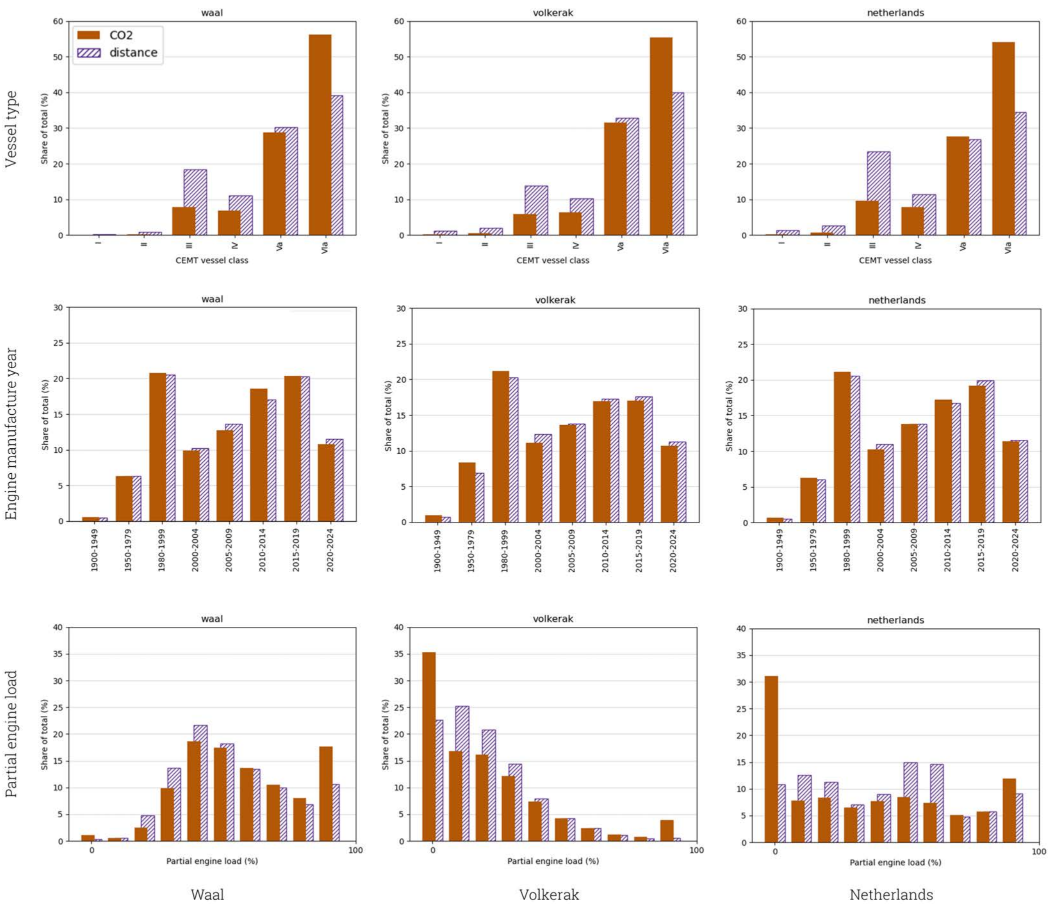

Figure 5.9: Understanding causes of emission patterns and hotspots

sions within the 0-10% power is produced while the vessel was actually stationary, and the vast majority is the result of idling vessels. The bottom chart shows how the emissions caused by stationary vessels were further broken down into duration categories, showing how many of them were caused during pauses of a certain length. The maximum length is 4 hours, since we assumed that above this threshold, all vessels have switched off their engine. Based on these charts, it can be concluded that assuming all vessels to switch off their engine after 2 hours, only results in less than 2% lower emissions.

Furthermore, we evaluated the sequence of activities performed by the vessels, to illustrate this perspective. In Figure 5.11, all trips between Antwerp and Duisburg were evaluated. The horizontal axis represents the route, with Antwerp on the left hand side (0 km) and Duisburg on the right-hand side (approx. 250 km).

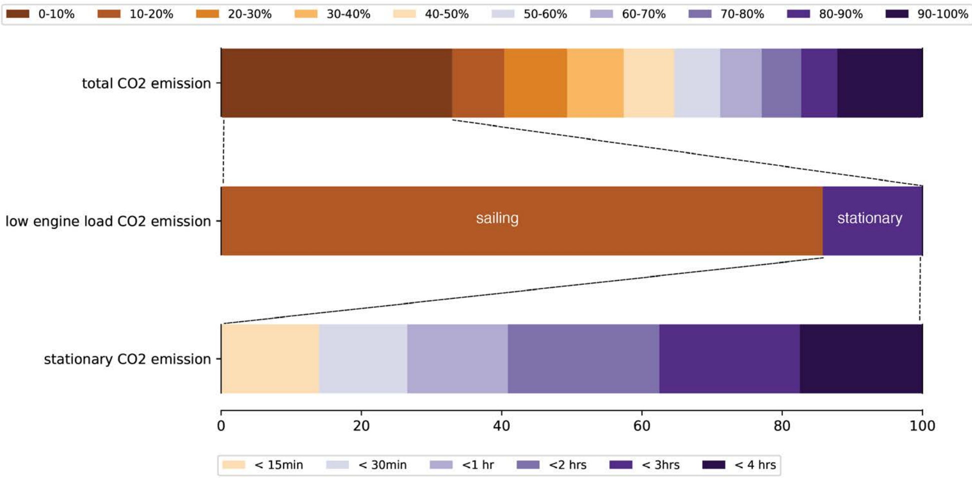

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Figure 5.10: Breakdown of emissions at three levels: (top) breakdown of total emissions into partial engine load bins, (middle) breakdown of emissions in the lowest bin into status, (bottom) breakdown of stationary vessels emissions into duration of pause

Thereby, the characteristics of the vessel trips in both sailing directions can be directly compared, whereby the Antwerp-Duisburg direction is indicated with solid lines and the Duisburg-Antwerp direction is indicated with dotted lines. In green, the plot presents the mean SOGs, obtained from the AIS-signal. In brown, the plot presents the mean speeds corrected for the current (STW). In purple, the plot presents the mean CO_2 emissions per sailed kilometre over the entire route.

On the left hand side, two lock complexes are encountered, being the Kreekrak and Volkerak locks, at 15 and 60 km, respectively. They come forward in Figure 5.11 through to the dip in mean speeds and the peak in emissions. Between these locks, the trip characteristics are very similar for both travelling directions. On this part of the route, current speeds are negligible, as the mean SOG is equal to the STW. However, a step change can be observed in the CO_2 emissions. This is triggered by a transition from shallow water to fairway segments having larger water depths. The right hand part of the figure, between 100 and 250 km, represents the river Waal. Here, we observe a difference between the SOG and STW. Vessels sailing against the current (direction Antwerp-Duisburg), have a lower SOG than vessel travelling in opposite direction. When correcting for the current, speeds in both directions become similar again, although vessels sailing upstream slightly increase power to overcome the current speed, refer to the brown lines in Figure 5.11. Additionally due to their longer travel time, vessels sailing upstream produce significantly higher emissions per travelled kilometre than those travelling downstream. Hence, Figure 5.11 demonstrates that vessels may adjust their behaviour to the (changing) environmental conditions, thereby influencing the emission performance.

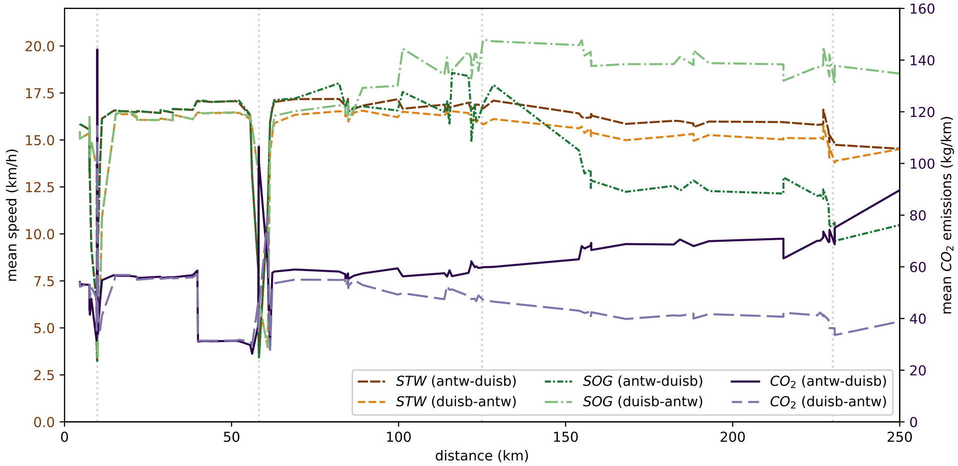

Figure 5.11: Analysis of vessels travelling between Antwerp and Duisburg, indicating the mean vessel STW (brown), the mean vessel SOG (green), and the mean CO_2 emissions (purple) for vessels sailing from Antwerp to Duisburg (solid) and from Duisburg to Antwerp (dashed). The vertical lines indicate the Kreekrak locks, the Volkerak locks, Gorinchem and Nijmegen from left to right.

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5.4. Discussion of the multi-perspective emission evaluation

5.4.1. Contribution to emission-reduction policy design

In Section 5.3.3 we demonstrated a couple of examples out of the large variety of visual outcomes that could be created based on the constructed event table. Based on these outcomes, we are able to address concrete policy-related challenges regarding inland shipping emissions in the Netherlands. For example: *What could be done to lower emissions in the identified hotspots?* By combining a scales perspective with a conditions perspective, this study underlines that different hotspots have different causes, and therefore, reducing these emissions requires location-specific policies. For example, we have shown that some hotspots occur near locks, where vessels spend a lot of time idling and maneuvering. Globally oriented policies invoking cleaner engines have a limited effect, due to the unfavorable power settings during slow sailing. However, targeted measures like optimising lock passage times for vessels may yield significant emission reductions locally. On the other hand, hotspots at busy rivers like the Waal may have only limited possibilities for emission reduction besides the global measure to renew (old) engines.

Elaborating further on potential measures, like those suggested above: *What is then the potential impact of fleet renewal?* The challenge is to understand the trade-off between the emission-reductions that can be achieved by renewing a particular (smaller or larger) share of the fleet, and the costs that are involved to do so. Referring to Figure 5.8, we found that, based on the latest emission factors for engine of a particular age (Ligterink et al., 2019), the potential CO_2 emission reduction is limited; even when replacing all engines manufactured before 2000, representing about a third of the fleet, would only potentially reduce those emissions with approximately 1.5 %. For PM_{10}, this balance is different; renewing only 6 % of the fleet's engines, would potentially reduce those emissions with approximately 12.5 %.

As stressed by (PIANC-InCom-WG234, 2023), which strategy works, varies from corridor to corridor, and even from fairway to fairway. So, *can the outcomes help identifying Green Shipping Corridor (GSC) or corridors with (at this moment) a higher potential for alternative energy sources?* Based on Figure 5.11, we can grasp the different characteristics of the fairways between Antwerp and Rotterdam, and those between Rotterdam and Duisburg. With multiple locks that need to be passed between Antwerp and Rotterdam, this system is characterised as 'closed'. As a consequence, current effects are absent, and when furthermore knowing the detailed bathymetry, resulting in accurate water depth predictions based on actual water levels, makes the energy use on the Antwerp-Rotterdam corridor more predictable than for the Rotterdam-Duisburg route. Moreover, the current on the Rotterdam-Duisburg corridor results in significantly different energy use profiles for upstream- and downstream-sailing vessels, thereby complicating the positioning of charging points or bunker locations. Based on these arguments, the Antwerp-Rotterdam corridor would have a higher potential for testing the use of alternative energy carriers. Note, that more specific distance-behaviour plots may be made, for individual vessels, or specific vessel types or groups on a specific corridor, for further understanding or comparison.

5.4.2. Discussion of the approach to determine shipping emissions

The availability of input materials and tools is a key driver for the obtained outcomes. The data sources and content of the data have resulted in a number of assumptions. These assumptions were regarding vessel characteristics and the emission estimation approach. The resulting limitations to the study are discussed in this section. To outline the impact of the limitations, we have used the event table to indicate the sensitivity of some of these assumptions, for example, for the assumed Weibull distribution for engine ages. To exploit the full potential of the approach in the assessment of inland shipping emissions, we have the following recommendations to reduce the uncertainties related to these assumptions.

The availability of anonymized AIS data has limited the possibilities for coupling vessel behaviour from the GPS-tracks to other sources of data, like vessel databases, including vessel dimensions, accurate engine characteristics and ages, and correct vessel operating draughts. Based on non-anonymised data, future studies could, furthermore, make an effort to couple vessel trips to transported cargo, allowing to express emissions in kilograms per tons-distance cargo. With more detailed data on the water depth, better conclusions regarding the influence of shallow water sailing sections on the total of shipping emissions can be drawn, and a more detailed connection with weather conditions could indicate the effect of weather conditions on the vessel behaviour (sailing speed or covered distance).

Future research should also expand the amount of data used in the analysis, i.e., the period covered by the AIS data, to improve the robustness of the observed patterns. This would require significant additional computational resources. The use of such resources was not warranted to demonstrate the workings of the method proposed here but would be recommended for a thorough policy management study.

Furthermore, an important limitation of the study is that the applied approach for resistance calculation was primarily developed for seagoing vessels, and therefore, it is less suitable for inland vessels and barges, having a higher block coefficient. Although the literature states that the incorporation of shallow water effects outweighs shape-related input uncertainties, future work should include undertaking further validation and investigating the extrapolation of the approach to vessels with higher block coefficients.

We have shown that the presented approach, using an event table and evaluating a system from several perspectives, is very suitable to address a range of other types of problems that consider complex systems whereby spatial variations influence the behavior and/or performance of an agent in the system, and where many different choices for interventions may be made. The evaluation of the inland shipping emissions is a relatively straightforward application since the attributes in the event table depend on a single vessel. Other applications might demand incorporating vessel-vessel interactions. For example, when considering nautical safety, AIS data can be used to evaluate distances and interactions between vessels. The event table is then required to capture the behaviors of vessel pairs instead of just individual vessels. When considering locking operations, the performance of the locking procedure strongly depends on the interaction of multiple vessels in the same locking cycle and their influence on each other's waiting times.

5.5. Chapter conclusions

Shipping related policies require an in-depth understanding of performance patterns at system level, supported by insights into underlying processes. The existing approaches to evaluate the inland shipping system (and many other systems) make it impossible to flexibly change perspective, between that of the entire system, and those capturing how individual or groups of agents behave and the conditions they encounter. By using the event-table scheme, we are now able to bring each of these perspectives together, making it straightforward to tie observations in one perspective (for example, spatial patterns on a map) to supporting explanations based on another perspective (for example, vessel speeds and their contributions to emissions). This provides an essential understanding of how the system works, and how the most promising improvements can be identified.

A thorough evaluation of the spatial emissions patterns on the Dutch inland waterways at various levels showed the important contributions of two phenomena: first, most hotspots are caused by large amounts of vessels sailing slow, running idle, or waiting, near locks and ports, and second, some hotspots occur at continuing rivers and channels with busy traffic at moderate speeds to full power. We presented the spatial patterns both for CO_2 and PM_{10} emissions, whereby the high-level views were similar. However, the policies related to reducing either of them are likely very different, firstly because CO_2 is much more considered at a global level while PM_{10} has a more concentrated (local) impact, and secondly because the PM_{10} reductions that can be obtained with engine renewal are much more significant than the CO_2 reductions for this measure.

In search of other potential measures, we found that a low engine speed setting is responsible for about a third of all CO_2 emissions, and further breakdowns indicated that only a minority share (15 %) of these emissions are caused by vessels that actually lay still. Hence, idling, slowing down, and maneuvering contribute significantly to the total emissions caused by inland vessels. We herewith shed light on the root causes of the inland shipping emissions, enabling data-driven or data-supported decision-making, instead of relying purely on expert opinions. By zooming in on the Antwerp-Duisburg corridor, we gained understanding of the role of infrastructure like locks, the influence of environmental conditions like currents, and the (adjusted) behaviour of vessels. Moderate current speeds can already cause CO_2 emissions per kilometre of upstream vessels to be a factor of 1.75 of the downstream vessels. Moving from relatively deep to shallow water cause a CO_2 emission increase of 50% when the vessel power is not adjusted.

Hence, our approach contributes to tackling the three identified challenges related to policy design for emission reductions. First, by taking different angles, a better understanding can be obtained of the implications that designed measures may have, both locally, and at the system level, as was discussed in Section 5.4.1. Second, the fact that spatial- and time-varying circumstances can be factored in, facilitates that measures and policies are better adjusted to local fairway characteristics. Third, having the obtained flexibility ensures well-understood operational profiles for individual vessels, groups of vessels, or routes that are required when developing new vessel technologies.

5.A. Vessel Energy Use Calculation

The basic idea of the approach is to estimate the total resistance (kN) that a vessel experiences for known vessel characteristics (length, beam, draught, vessel SOG) and fairway properties (channel width, depth and ambient current). Following the empirical approach of Holtrop and Mennen (1978), the resistance is estimated through a summation of the frictional resistance R_F, the appendage resistance R_{app}, the resistance due to the generation of waves R_W, the residual resistance R_{res} and the ship-model correlation resistance R_A, as indicated in Equation 5.1. Furthermore, $(1 + k_1)$ represents the form factor introducing the viscous resistance component. Shallow water corrections were made in the frictional resistance and in the wave resistance. Note that these corrections can only be applied if both the instantaneous vessel SOG, the local water depth, and the current speed at that moment in time are known.

$$R_{tot} = R_F(1 + k_1) + R_{app} + R_W + R_{res} + R_A \tag{5.1}$$

The effective horse power P_e is the power required to overcome the vessel resistance R_{tot} based on the vessel's STW V_0, refer to Equation 5.2. Accounting for the losses at the propeller, shaft and gearbox results in the break horse power P_b that the engine should deliver. Refer to Equation 5.3, whereby η_t and η_g are the transmission and gearing efficiencies respectively, and η_0, η_r and η_h are the propeller open water efficiency, the relative rotative efficiency and the hull efficiency, respectively. All efficiencies were assumed constant and independent of the considered vessel. Adding the hotel power to the break horse power results in the total power P_{tot} (Equation 5.4), whereby the hotel power is estimated constant at 5% of the installed engine power.

$$P_e = V_0 \cdot R_{tot} \tag{5.2}$$

$$P_b = P_e \left(\frac{1}{\eta_t \eta_g}\right)\left(\frac{1}{\eta_0 \eta_r \eta_h}\right) \tag{5.3}$$

$$P_{tot} = P_b + P_{hotel} \tag{5.4}$$

The product of the total power and the duration Δt that it needs to be delivered yields the energy E (kWh) that is associated with that sailing event:

$$E = P_{tot} \cdot \Delta t \tag{5.5}$$

The vessel weight class combined with the engine age result in an estimate for the general emission factor EF_{gen} (Ligterink et al., 2019). Furthermore, estimates of the partial engine load, calculated as power demand over installed power were used to determine an emission correction factor EF_{corr}, to capture the effect that engines produce more emissions when they are run outside their optimal operating specification. These emission factors are used to estimate the potential emission EM of green house gasses (i.e. CO_2) and other environmental pollutants (i.e. PM_{10}, NO_X), refer to Equation 5.6. We state 'potential' emissions, since actual emissions depend on the installation of mitigating measures, like scrubbers and filters.

$$EM = E \cdot EF_{gen} \cdot EF_{corr} \tag{5.6}$$

6

Discussion

Un re-route the rivers
Let the dammed water be
There's some people down the way that's thirsty
Let the liquid spirits free

Gregory Porter

This study started with the formulated desire to incorporate multiple perspectives on a system in a single analysis. Thinking through how a system is conceptualised, how it is represented, upfront of an actual analysis, helps achieving a basis for addressing all questions that are likely to be asked about that system from different domains of disciplinary backgrounds. The introduced framework is a proposal for such a conceptualisation step. This section discusses a reflection on the adopted framework, its limitations, and possibilities for generalisations. Specifically, the multi-perspective approach and the formulated set of perspectives (Section 6.1), the challenges related to generating concrete outcomes (Section 6.2), and the added value to the decision-making process (Section 6.3) are considered. Finally, Section 6.4 zooms out to consider non-nautical applications.

6.1. From Isolated Views to Integrated Perspectives

Looking at a problem from multiple perspectives is not new. Many studies aim at increasing knowledge about a system by taking different angles, for example, a technical and an economical, or a microscopic and a macroscopic. Systems science acknowledges the many different ways of how a system is seen, and how it can be represented, resulting in corresponding approaches to incorporate multiple perspectives (Smyth and Checkland, 1976; Bunge, 1979). The diversity of considered systems subsequently diversified the concrete analysis approaches for real-world applications. So, although looking from multiple perspectives, because particular disciplinary-driven approaches are used for individual perspectives, it is difficult to unite everything later on. This comes forward in the challenge to connect the behaviour of the system to the environment it is situated in (Lukyanenko et al., 2022), for example.

To really have multiple analysis perspectives complementing each other, requires integrating them, being a long-standing challenge (Singer Jr, 1959; I. Mitroff and Linstone, 1993; Hall et al., 2005). Their common basis was sought for, beyond disciplinary- or domain-specific frameworks, and starting from all (or at least, many) questions one could ask about the evaluated system. An important scope reduction in this thesis was the explicit consideration of physical systems only, addressing systems with moving agents in particular. Focusing on physical systems specifically, enabled reducing the level of abstraction, and tightening the link to implementation through the design of an event table.

The similarities of the independently formulated perspectives of Scales, Conditions, Behaviour and Dependencies with the existing Composition, Environment, Structure, Mechanism (CESM) model (Bunge, 1979), indicate alignment with the literature. The differences mostly come forward due to the focus on concrete, physical system analysis. Where the CESM model considers the last perspective of Mechanisms only in case of concrete systems, the Scales perspective (absent in the CESM model), being the primary considered perspective in our framework, takes a physical system as a starting point. This perspective prescribes both the (spatial and temporal) scope and resolution of the system representation, forming an important basis for the integration of the perspectives. The choices about the highest level of detail, or event level, made as part of the Scales perspective, correspond to the level at which the connection is made between system agents (components) and its environment. In other words, how detailed do we want to be when describing the conditions for an agent in terms of area or time frame? These choices also resonate in the consideration of the Behaviour perspective, directing the level of detail for distinguishing separate agent actions.

Is the set of perspectives complete? Based on the limited number of application cases considered, it is impossible to definitively conclude that. The cases show that the perspectives form a solid basis for formulating requirements about the data sources and analysis techniques, in view of the analysis objectives. But, as these objectives were also considered following the same perspectives, it is well conceivable that in the future, questions about the system arise that are not strictly part of either the Scales, Conditions, Behaviour, or Dependencies perspective. However, as the event table integrates the four perspectives and associated concepts into a holistic view on the system, it is possible to evaluate it from a new perspective later. Hence, applying this framework does not explicitly limit analyses to the identified perspectives only, it helps anticipating potential new perspectives in the future.

6.2. From Theoretical Perspectives to Concrete Outcomes

The perspectives jointly ensure that a holistic view can be derived based on available input materials. The resulting event table is the basis for this, capturing the concrete outcomes suitable for multi-sided inspection. To achieve such a result that fulfills the specified analysis goals, much depends on the availability of data sources, data-science techniques, and (computational) facilities. Considering this balance upfront helps deciding to either adjust the objectives, or to put more effort into finding adequate materials. Several data science techniques were outlined in Chapter 3 that support turning theoretical goals into the concrete outcomes in a more efficient, effective, or faster way. Scaling up computations is an important prerequisite to extend the scope, and/or to increase the detail level. The corresponding approach with *Dask* (Chapters 3, 4, and 5), was executed using the Planetary Computer, the cloud computational facility of Microsoft. Unfortunately, this functionality was terminated in the summer of 2024. Various alternatives (see for example Calkoen et al. (2025)) were considered, weighing in criteria like learning curve, capacity, costs, and the connection with data storage. This development demonstrated how calculation procedures can be integrated with facilitating platforms, and it underlined the challenge of remaining flexible to move to an alternative facility without much effort.

Another challenge is related to restrictions for cases or data sets in particular, having the consequence that information explicitly remains uncoupled. For example, working with sensitive personal data requires adhering to laws and regulations regarding privacy. To exploit the full potential of data while guaranteeing the moral and secure use thereof, several privacy-preserving methods have been and are being developed (for an overview, see Panchal et al. (2024)). In each of the presented cases in this thesis, the AIS-data was anonymised, meaning that vessel identification numbers were replaced by dummy values. In the emissions-case (Chapter 5) this meant that it was not possible to couple detailed vessel characteristics from inland-vessel databases to the trajectories that were derived from the AIS-data. Therefore, based on dimension- and type-information and publicly available information, estimates were derived for the required characteristics.

One can imagine that for safety monitoring (Chapter 3) this restriction is even more important. Here, coupling vessel behaviour to more background knowledge about the vessel (port of departure, flag state, cargo, etc.) can be essential to identify anomalous behaviour, or to distinguish between "just odd" and "dangerous". Clearly, in view of this case, there is a difference between a scientific phase and an operational phase. The goal in the scientific phase is to outline the possibilities and challenges that do not necessarily require the most sensitive data. In an operational phase, being in a protected environment, improving nautical safety may outweigh these privacy-related restrictions.

To take a step from scientific to operational phase, an attempt was made to demonstrate the added value of using non-anonymised data and couple it to other sources. Hereby, we proposed and tested a solution whereby our algorithm was sent to and run locally at the data provider, instead of the data provider sending the data. The benefit of running the algorithm locally at the data provider, was that the coupling between the databases could be internally, and the original data could be used for that. Moreover, by locating the entire data processing there, only non-sensitive (aggregated or anonymised) outcomes would have to be exchanged. Although technically this approach proved suitable for implementation, practically, the difficulty is to design and install the adequate quality checks and procedures for running externally developed algorithms on sensitive data in an internal environment, which was still an obstacle at the time of this study's execution.

6.3. From Comprehensive Outcomes to Informed Decision-Making

The ultimate objective of the performed analyses is that they should serve well-supported decision making when improving systems. The outcomes of modeling or data-analysis efforts must be easy to interpret, and actionable. As indicated by among others Biswas (1975) and Coussement and Benoit (2021), an important emphasis should be on making outcomes of (modern) analysis techniques readily understandable to decision makers, or translating them into understandable terms. Hence, there should be good agreement between what decision makers need, and what the outcomes offer.

The added value of explicitly considering different perspectives upfront of an analysis is twofold. First, it helps managing expectations regarding achievable objectives, and inventorising how making available additional materials or methods contributes to making better decisions. Second, with the same materials, a much broader understanding can be gained based on the outcomes, simply by looking at them from various angles. During a set of workshops (July 10th, 2024, see Appendix A of van den Heuvel (2024)) we considered the monitoring case (Chapter 3) and the nautical safety case (Chapter 4), wherein discussions were initiated based on (early stage) analysis outcomes. Experts from the Dutch Coast Guard, Maritime Research Institute Netherlands (MARIN), Deltares, and Rijkswaterstaat were presented various outcome visualisations, offering them the opportunity to ask follow-up questions. Consequently, the questions were both related to understanding the analysis (the *how?*, i.e., "how was the probability determined of drifting into a wind park?"), as to understanding the outcomes (*why?*, i.e., "why are the probabilities larger for Southwesterly winds?").

The event table that was used as a basis for the visualisations was sufficient to generate different, new visualisations, for example by zooming in on local details, filtering specific conditions, or by aggregating by particular contributing factors. Importantly, no new data processing efforts were required, as it considered taking different cross sections of the table only. This starting point, having all outcomes and presentations thereof having that common ground, enables that different viewpoints actually complement each other.

Although both considered cases have clearly different objectives, the framework could be successfully applied for each of them. The characteristics of the event tables for the allisions and the emissions case are presented in Table 6.1. It shows their different spatial basis, e.g., grid versus graph, and their different system performance objectives. In both cases, the event table was several million rows long, which is drastically influenced by the choices for scope and detail level. For example, using a more refined grid will automatically increase the number of events. The allisions case has a large number of columns because it contains all intervention measure scenarios and the resulting allision probabilities expressed per additional drifting hour. In both cases, Python modules were used to make calculations at the individual vessel level, focussing on the drift path for the allisions, and on the energy use for the emissions. The framework supported bringing this to a system level for which aggregated performances were determined, while keeping the underlying detail levels available in the event table.

	Allisions	**Emissions**
Number of rows	6.2 million	10.1 million
Number of columns	260	52
Spatial structure	grid	graph
Size of spatial structure	16,832 cells	14,361 edges
Performance indicated by	probability of allision	masses of emissions
Used Python module	*OpenDrift*	*OpenTNSim*

Table 6.1: Comparison of the event tables generated for the allision and the emission application cases

What the cases considered in this thesis demonstrate jointly, is that there can be many different viewing points to a single event table created with the framework. For example, in each of the cases, the event table allows both a strategic and an operational interpretation. From a strategic standpoint, the event table for the emissions case reveals that emission-reduction policies targeting slow-sailing vessels can be very effective, while it can also be used to establish operational profiles of vessels or fleets, supporting vessel owners. From an operational standpoint, the event table for the nautical safety case can support day-to-day deployment decisions for emergency response vessels in view of expected metocean conditions, while it can also support strategic decision-making about the number of required emergency support vessels to be invested in. Finally, although mostly considered from an operational standpoint, where the event table related to nautical monitoring is used to identify anomalous behaviour, at a strategic level, it can be used to identify leading indicators for accidents (as opposed to lagging indicators formed by historical accident data), providing better insight into the locations and conditions with high risks on accidents. Besides this broad applicability range, the fact that all perspectives have the same basis increases the possibilities for discussions about the system among different stakeholders.

6.4. Perspectives on Perspectives

A central starting point of this thesis was the existence of different worldviews and the corresponding representations of reality. This will also reflect on the use of the framework developed and presented in this thesis. Hence, analysts with different disciplinary backgrounds will have different perspectives on the perspectives. But even within a single discipline, different analysts will have different considerations for accepting or rejecting available input materials, and they can likely create a different event table design, even given the same starting point.

What will this framework achieve in the context of decision-making in (complex) systems, and what not? As indicated, applying the framework should not be seen as a means to standardise or uniform approaches to evaluate these systems. Neither does it lead to a single best or optimum method. So what is the added value, when the framework results in varying representations of reality? The most important benefit is the fact that the problem *is* analysed from multiple perspectives, with a thorough consideration of the objectives. Although this leads to decisions about incorporated materials and methods, applying the framework makes the considerations explicit and transparent. A discussion about these considerations can, moreover, take place upfront of time-consuming and intensive computational processes, which may lead to target adjustments or modifications to the materials and methods.

Zooming out from the applications of this thesis (nautical systems) to all potential applications of this framework having the same characteristics (physical, agent-based systems with high complexity), the question is, whether the same benefits can be obtained. In the medical field, various systems can be found that have the same characteristics, of which examples are given in Chapter 2. For example, publications regarding the COVID-19 outbreak can be connected to the framework by categorising them by analysis perspective. From the Scales perspective, the temporal and spatial infection rates have been evaluated (Parvin et al., 2021; Purwanto et al., 2021). From the Conditions perspective, research has investigated the influence of meteorological conditions, but also other circumstances like population density (R. Zhang et al., 2020; Hossain et al., 2024) on the spread of the virus. From the Behaviour perspective, the effectiveness of several behavioural measures have been considered, like social distancing, wearing face masks, or quarantining (Ngonghala et al., 2020; Johansson et al., 2021). From the Dependencies perspective, one can evaluate the infection rate of one region subject to the infection rates of neighbouring regions (Tabera Tsilefa and Raherinirina, 2024).

Several of the above-mentioned publications indicate how insights that we classified to be of a different perspective, can enrich their outcomes. For example, Purwanto et al. (2021) mention how considering circumstantial conditions (Conditions perspective) can be useful to better explain their (Scales perspective). Johansson et al. (2021) indicate how (Behaviour perspective) virus-spread reduction measures should be evaluated in space and time (Scales perspective) in order to implement them effectively. Our framework can accommodate this by expressing perspective-related objectives for the problem. By explicitly considering upfront what we would like to know about each perspective, may lead to a different (but not necessarily more complex) approach. For example, keeping track of space and time may not be done automatically, but it can be the basis for coupling many other sources of information, such as environmental conditions or policy measures that vary in time and space. The framework helps to point out this added value, and it enables us to make well-supported choices about the required resolution.

6.5. Recommendations

One of the questions we asked ourselves was "is the set of perspectives complete?" Comparison with other multi-perspective approaches may point out viewpoints that were not explicitly considered, however, the integrated outcome based on this defined set of perspectives can likely still extract the desired view. Therefore, it is more interesting to consider other cases to apply the framework to, i.e., putting it to the test. Primarily, the focus should be on agent-based systems, such as shipping, but in a broader sense, any means of transportation qualifies. When expanding the scope further, considered cases could include migration or medical (as indicated in Section 6.4) applications.

Besides considering the set of perspectives, it is recommended to further investigate the concrete design requirements generated for the event table. As also outlined in Section 6.4, how the event table looks exactly, may vary between different analysts. Considering more applications of the framework can indicate these differences, and may drive an improved description of the event table requirements following from the perspectives.

In terms of data science, developments are made at a fast pace. It was shown that the framework can be united with the latest developments. It is recommended to explore the increased possibilities of scaling up computations, using more, and larger datasets. Incorporating larger datasets has large potential to improve the understanding of the considered system; analysing longer time periods, larger areas, higher detail levels, and with increased complexity. Incorporating more datasets, must be done with awareness of potential privacy issues. To enable coupling of multiple sets may require more potentially privacy-sensitive data. Moreover, as more datasets are merged, the chances increase that the merged dataset can be used to derive privacy-sensitive information from. In this light, privacy-enhancing techniques (Panchal et al., 2024) should be considered. Furthermore, running algorithms in-house with the data provider can still be considered as a solution, if an acceptable procedure can be developed for the exchange and running of the algorithms.

For the application cases in this dissertation, several recommendations are made below, for making (efficient) use of technological developments to improve the outcomes:

Monitoring In the monitoring application, it is recommended to target a higher computational performance, being able to process more data in shorter time. This is needed to finally achieve real-time analysis, which is needed to detect anomalous behaviour on the spot. Another recommendation is to make labelled datasets available, or to develop them. Having such sets available makes it possible to apply supervised ML techniques, that can support detection of dangerous, suspicious, or explainable behaviour, instead of just anomalous behaviour.

Allisions In the allisions case, it is recommended to consider consequences, instead of probabilities only, as was done in Chapter 4. Essentially, one would have to merge the current sets of data and model outcomes, with another dataset, whereby similar distinctions are made between scenarios, refer for example to IV-Infra (2025). Merging these kinds of datasets has been considered already in each of the cases, and brings no new technical challenges. However, incorporating the qualitative consequence descriptions into the risk analysis is an important step for future study. Furthermore, the assembled event table can be improved by improving failure probabilities under various conditions and for various vessel types. Further validation studies for *OpenDrift* are also recommended, and improving its predictive capabilities based on the outcomes.

Emissions In the emissions case, it is recommended to analyse longer time periods, to provide improved understanding of seasonality, and to link global patterns to local disturbances. Furthermore, and also based on an availability of more data, the application of ML techniques should be explored further. These ML approaches can be complementing or used instead of the energy-estimation approach that was applied in Chapter 5. The potential of for example Long Short-Term Memory Networks was demonstrated by Tijdeman (2024).

A large share of this study and the accompanying recommendations address scientific research: further development of theoretical frameworks, improving computational performance, technically facilitating state-of-the-art data science. However, the developed framework may also extend the view of policy makers or other decision makers for (complex) systems. It would be highly encouraged to discuss the four perspectives on any problem, before transferring an analysis assignment to scientists. Doing so, following the developed framework, can help understanding the balance between research targets and the availability of materials and methods, without needing to understand the approach in-depth. It may aid discussions and result in sharper definitions of research aims, and help understanding the outcomes once the analysis is finalised.

7

Conclusions

Once you're free of mind about the concept of
harmony and of music being "correct"
You can do whatever you want
So, nobody told me what to do
And there was no preconception of what to do

Giorgio Moroder, Guy Manuel Homem Christo, Thomas Bangalter

Changing perspective broadens the view, and may open up the road to new approaches or solutions that were not even considered before. Also in relation to nautical systems, being the focus of this thesis, it was found that using multiple "lenses", instead of just one, is of added value in the analysis of these systems. Making decisions for improving these systems is challenging, because of their complexity: it is difficult to oversee all consequences of implemented measures. Using a particular lens results in a simplified representation of reality, but potential aspects of the system may not surface. By switching lenses easily and keeping the connection between the resulting views, it is more likely that all aspects of the system become known. In lack of an approach to incorporate multiple perspectives for the analysis (data analysis or modelling) of nautical systems (or similar), the objectives were to identify the relevant perspectives (the appropriate lenses to look through), and to determine how to merge them into an integrated whole (a combined image based on multiple lenses). The developed multi-perspective framework encompasses both objectives and provides the necessary guidance to tailor and apply it to a specific use case.

7.1. Merging Perspectives for Nautical Systems

The used perspective influences both how analysis objectives are formulated and how input data sources are selected. To improve the comprehensiveness of system analyses, it is therefore important that multiple perspectives are considered that jointly provide a complete image of the nautical system. Which perspectives to consider, was the focus of the first research question:

1. *Which perspectives on nautical-system analysis objectives should be considered to derive corresponding requirements for the data and tools?*

The following four defined perspectives provide a complete view of a system:

Scales Objectives related to the scales perspective consider the "where" and "when" aspect of how a system performs, often represented by spatial distributions on maps, or temporal trends. In terms of data sources, these objectives demand a certain resolution that allows for browsing in space and time, as well as a structure that ties detail levels to higher levels up to the system level. Parallelisation techniques allow scaling up computations, offering larger scopes, detail levels, and complexity levels to be evaluated efficiently.

Conditions From the conditions perspective, analysis objectives consider the influence of circumstantial factors, like the environment, on the performance of the system. To achieve these objectives requires data about the circumstances under which the system or individual components of it, operate. This perspective outlines the choices to be made around merging data sources of different temporal and/or spatial resolution, or the connection level with the agents, and the corresponding algorithms.

Behaviour The objectives from the behaviour perspective encompass observing the sequence of actions by agents (individually or collectively) and to unfold these sequences into behaviour that can be evaluated for its effect on the system.

Hence, the (individual or collective) actions of agents need to be distinguished by the data sources. For identification of (unknown) behaviour (categories), ML techniques are very suitable.

Dependencies The dependencies perspective entails objectives to identify causal relationships in the system, and to determine critical paths, resulting from interdependencies of processes or between agents. These objectives pose complex requirements to the data sources. For example, the action causing another action (effect) needs to be explicitly documented as such. For ML-techniques to establish cause-and-effect patterns, this requires data to be labelled (e.g., only known behaviour can be considered).

The four formulated perspectives, in the above order of appearance, build on to each other, i.e., their requirements are cumulative. This means, for example, that the Behaviour perspective cannot be evaluated in complete isolation; it requires that the Scales and Conditions perspectives are considered as well, including fulfilment of the associated requirements.

Using multiple perspectives to evaluate a system is more commonly done as part of Systems Theory. However, the concrete implementation of such frameworks, in particular on how to integrate the various views, has been a remaining challenge. This challenge was faced as part of the second research question:

2. *What concept can facilitate merging multiple analysis perspectives into an integrated whole?*

The introduced event table provides the concrete basis wherein the four perspectives can be united. Where isolated perspectives, or specific disciplinary approaches have a particular associated concept to represent a system, the event-table concept facilitates incorporation, and merging, of multiple concepts. Using a table format is necessary, because it provides the possibility to aggregate (which is important for uniting all perspectives into global pattern and overall views), as well as to filter (which is important for extracting different perspective and detail views). An event table is unique due to its capability to combine spatial and temporal data (using moving-features principles) with an event-based structure that can accommodate processes expressing agent behaviour and dependencies between distinct activities. The two considered nautical cases, that were significantly different in terms of their objectives, considered area, data sources, and calculation approaches, have demonstrated that the event-concept succeeds in uniting the requirements of various nautical system analyses, using the defined perspectives as a starting point. Moreover, the event table proved successful as a basis for evaluating the system from various, complementing perspectives.

7.2. Complementing Computational Techniques

Considered upfront of the actual analysis, the framework is used to balance analysis objectives against the available materials and methods. Hence, expanding the possibilities on the input side, likely results in expanding the analysis objectives in terms of scope, detail level, or complexity level. Therefore, the third research question was considered:

3. *How can data-science techniques broaden the applicability of the perspectives in the framework for nautical safety monitoring at the Dutch North Sea?*

The developments of more and more data becoming available, the expanding computational capacity, and the rapid improvements of data-analysis tools, ML in particular, jointly offer opportunities to deepen the understanding of (nautical) systems. Having (big) data available may ensure looking at a system at a certain scope and detail level, but it may be an inefficient or time-consuming process in absence of the right tools. For the safety monitoring of vessel traffic at the North Sea, operators rely on many sources of information. It therewith serves as a suitable case study to demonstrate how the above-mentioned developments go hand-in-hand with the presented framework.

In view of this case, four data-science techniques contribute to more (time-)efficient computational processes to construct an event table following the perspective-related requirements. First, scaling up computations requires trajectorising AIS-data, such that the sequence of operations for each resulting set can be conducted in parallel. Second, coupling vessel behaviour to locally varying factors (the operating environment), requires smart merging of multiple data sources, with different structures and resolutions. Third, identifying anomalous behaviour requires evaluating many characteristics about the vessel, its behaviour, and the conditions. Using dimension reduction (a ML-application), these many characteristics can be reduced to a measure of similarity between all trajectories, presented on a two-dimensional canvas. Importantly, interpretation of these trajectories, and subsequent identification of anomalies, can only be done by again unfolding these 2-dimensional representations to actual characteristics and behaviour. Fourth, understanding causalities, improving early detection of anomalies, requires labelling and classifying known behaviour, which is an effort foreseen for future work.

7.3. Broadening Nautical Analyses

Two real-world problems have been considered, whereby two aspects are important. First, they should demonstrate the capability of the framework to merge multiple perspectives into a single data structure. Second, they should demonstrate the added value of such a data structure for the outcomes in the light of decision making and policy design.

4. *How can generating an event table through the multi-perspective framework improve the assessment of allision risk-mitigating measures at the Dutch North Sea?*

Application of the multi-perspective framework has contributed to an improved transparency of the risk analysis, because of the event table foundation. Upfront consideration of the defined perspectives creates the indispensable awareness to evaluate the risks circumstance-wise (e.g., explicitly considering combined location-, environment-, and vessel-scenarios). Hereby, it is possible to zoom in on individual scenarios, each of which consist of conditional probabilities with respect to these circumstances. This ability supports the discussion of expert judgement on risks, for concrete scenarios. Consequently, these qualitative risk assessments become more insightful and their impact can be traced back, contributing to the risk analysis as a whole becoming more transparent. Moreover, being able to couple threats (potential drifting vessels) with intervention measures is a vital competency move from the performance of the system (the risk levels without additional interventions) to the identification of effective mitigation measures.

For this case, applying the introduced framework has multiple benefits for decision making. Strategically, it supports spatial design choices, for example regarding the size of buffer zones between shipping lanes and wind parks, or regarding the number of emergency response vessels required to cover an adequate area within reasonable time (e.g., before ships drift into a wind park when they lose control). Therewith, these insights are important to policy makers and executive agencies, for example. Operationally, it supports deriving deployment strategies of emergency response vessels, considering instantaneous or predicted meteorological and oceanographic conditions, being important insights to the Coast Guard in their day-to-day planning of operations.

5. *How can generating an event table through the multi-perspective framework improve the design of effective emission-reduction measures for the Dutch inland nautical system?*

Applying the multi-perspective framework to the case of inland shipping emissions highlighted the benefit of keeping track of time and space. Importantly, this insight was established prior to any conducted computational process. Considering both the Scales and Conditions perspective motivated the mapping of vessel tracks onto the inland waterway network, opening up the opportunity to tie local conditions to local behaviour, and local consequences. Furthermore, the hierarchic spatial structure enabled aggregation. These explicit considerations enabled a flexible movement between views with global emission patterns, and views with detailed identification of emission sources.

Although it is known that engines run less efficiently at lower speeds, the significant share of the total emissions caused by slow-sailing vessels has only become clear by complementing these global patterns with a detailed breakdown of the emissions into engine running speed categories for the entire fleet. Being able to quantify the contribution of these shipping behaviour categories (slow sailing, idling, manoeuvring) reveals high-potential emission-reduction measures, like improved lock and bridge operating strategies, or technical solutions like hybrid (diesel-electric) propulsion systems that allow using batteries during manoeuvring. Furthermore, complementing vessel behaviour insights with local conditions reveals how captains react to changing conditions such as river current speeds. This knowledge can be used by shipping companies to optimise their sailing schedules chasing a reduction of the overall fuel (or energy) consumption.

7.4. Merging Multiple Perspectives to Extend Views

The above conclusions for the research questions outline that multiple perspectives on a system can be merged into a single data concept called an 'event table', and that doing so, improves the decision-making process to develop improvement measures for real-world nautical cases. The four defined perspectives jointly establish a comprehensive view of the system. Bringing them together into a single data structure introduces demonstrable flexibility to the system analysis. It connects causes to global patterns, it connects scenario-specific uncertainties to system performance, and it connects collective behaviour to unique outliers. For every case, the desired connections may be different, but application of the framework ensures that the right considerations are made upfront of starting (intense) computations. Consequently, the outcomes facilitate addressing the questions relevant for decision making and policy design, even if some of the questions were not explicitly asked upfront of the computational process.

7

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List of Abbreviations

ABM Automated Behaviour Monitoring. 37, 45, 48

AIS Automatic Identification System. 5, 13, 26, 27, 30, 37–40, 42, 43, 45, 48, 49, 60, 66, 68, 72, 74, 87, 93–95, 97–101, 110, 111, 117, 128

CEMT Conférence Européenne des Minstres de Transports. 96, 98

CESM Composition, Environment, Structure, Mechanism. 116

CRS Coordinate Reference System. 42

DBSCAN Density-Based Spatial Clustering of Applications with Noise. 37

DGDR Dutch Government Data Register. 40

ECMWF European Centre for Medium-Range Weather Forecasts. 41, 69

EMSA European Maritime Safety Agency. 37, 45, 48

ERTV Emergency Response Towing Vessel. 66, 70, 78, 79, 81, 84, 86–88

EU European Union. 64

FIS Fairway Information System. 96–100

FSA Formal Safety Assessment. 64

GIS Geographic Information System. 16, 17

GM Metacentric Height. 58

GSC Green Shipping Corridor. 110

GTSM Global Tide and Surge Model. 69

IMO International Maritime Organisation. 40, 64, 68, 92, 95

LNG Liquefied Natural Gas. 93

LOF Local Outlier Factor. 52, 53

MASS Maritime Autonomous Surface Ships. 28

ML Machine Learning. 9, 11, 12, 32, 122, 127, 128

NRA Navigation Risk Assessment. 64

NUC Not Under Command. 58, 65, 67, 76, 79, 86

OSM OpenStreetMap. 45, 49

PCA Principal Component Analysis. 51

SFC Specific Fuel Consumption. 95

SMM Safety Management Manual. 58

SOG Speed Over Ground. 99, 100, 108, 109, 113

STW Speed Through Water. 93, 100, 108, 109, 113

TSS Traffic Separation Scheme. 40, 50

UK United Kingdom. 64

UMAP Uniform Manifold Approximation and Projection. 51

UST Unbounded Systems Thinking. 10

WCSS Within Cluster Sum of Squares. 52

xAI eXplainable Artificial Intelligence. 32

References

Ackoff, R. L. (1971). “Towards a System of Systems Concepts”. In: *Management Science* 17.11, pp. 661–671. DOI: 10.1287/mnsc.17.11.661.

Ahamad, N. B. B., J. M. Guerrero, C.-L. Su, J. C. Vasquez, and X. Zhaoxia (2018). “Microgrids Technologies in Future Seaports”. In: *2018 IEEE International Conference on Environment and Electrical Engineering and 2018 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe)*. Institute of Electrical and Electronics Engineers Inc., pp. 1–6. ISBN: 978-153865185-8. DOI: 10.1109/EEEIC.2018.8494428.

Akoka, J., I. Comyn-Wattiau, N. Prat, and V. C. Storey (2024). “Unraveling the foundations and the evolution of conceptual modeling—Intellectual structure, current themes, and trajectories”. In: *Data & Knowledge Engineering* 154, p. 102351. ISSN: 0169-023X. DOI: https://doi.org/10.1016/j.datak.2024.102351.

Alessandrini, A., P. Argentieri, M. A. Alvarez, T. Barbas, C. Delaney, V. F. Arguedas, V. Gammieri, H. Greidanus, F. Mazzarella, M. Vespe, and L. Ziemb (2014). “Data Driven Contextual Knowledge from and for Maritime Situational Awareness”. In: *Proceedings of the 1st International Workshop on Context-Awareness in Geographic Information Services*. CAGIS.

Algavi, Y. M. and E. Borenstein (2023). “A data-driven approach for predicting the impact of drugs on the human microbiome”. In: *Nature Communications* 14.1, p. 3614. DOI: 10.1038/s41467-023-39264-0.

Andrienko, N. and G. Andrienko (2013). “Article Visual analytics of movement: An overview of methods, tools and procedures”. In: *Information Visualization* 12.1, pp. 3–24. DOI: 10.1177/1473871612457601.

Antão, P., S. Sun, A. Teixeira, and C. Guedes Soares (2023). “Quantitative assessment of ship collision risk influencing factors from worldwide accident and fleet data”. In: *Reliability Engineering & System Safety* 234, p. 109166. DOI: https://doi.org/10.1016/j.ress.2023.109166.

Asahara, A., H. Hayashi, N. Ishimaru, R. Shibasaki, and H. Kanasugi (2015). “International Standard “OGC Moving Features” to address “4Vs” on locational BigData”. In: *2015 IEEE International Conference on Big Data (Big Data)*. IEEE, pp. 1958–1966.

Aven, T. (2010). “On how to define, understand and describe risk”. In: *Reliability Engineering & System Safety* 95.6, pp. 623–631. ISSN: 0951-8320. DOI: https://doi.org/10.1016/j.ress.2010.01.011.

Baak, J. (2023). “The ship domain in port areas: A case study in the Port of Rotterdam”. MA thesis. Delft University of Technology. URL: http://resolver.tudelft.nl/uuid:02b5f319-d825-48cb-b902-84fd71676a71.

Bach, B., P. Dragicevic, D. Archambault, C. Hurter, and S. Carpendale (2017). “A Descriptive Framework for Temporal Data Visualizations Based on Generalized Space-Time Cubes”. In: *Computer Graphics Forum* 36.6, pp. 36–61. DOI: https://doi.org/10.1111/cgf.12804.

Bag, R., M. Ghosh, B. Biswas, and M. Chatterjee (2020). “Understanding the spatio-temporal pattern of COVID-19 outbreak in India using GIS and India’s response in managing the pandemic”. In: *Regional Science Policy and Practice* 12.6, pp. 1063–1103. DOI: 10.1111/rsp3.12359.

Bahmani, B., B. Moseley, A. Vattani, R. Kumar, and S. Vassilvitskii (2012). “Scalable K-Means++”. In: *Proceedings of the VLDB Endowment (PVLDB)*. Vol. 5. 7, pp. 622–633. DOI: 10.48550/arXiv.1203.6402.

Bakker, F. P., S. van der Werff, F. Baart, A. Kirichek, S. de Jong, and M. van Koningsveld (2024). “Port Accessibility Depends on Cascading Interactions between Fleets, Policies, Infrastructure, and Hydrodynamics”. In: *Journal of Marine Science and Engineering* 12.6. DOI: 10.3390/jmse12061006.

Bakker, F. and M. van Koningsveld (2024). “Tool to evaluate countermeasures at locks to limit freshwater losses and saltwater intrusion while minimizing waiting times for shipping”. In: *Proceedings of the 35th PIANC World Congress, 29 April – 23 May 2024*, pp. 1558–1563.

Bakker, F. P. (2025). “Quantifying water transport performance in estuaries - An agent-based method to facilitate system modification trade-offs in multi-stakeholder settings”. PhD thesis. Delft University of Technology. URL: https://resolver.tudelft.nl/uuid:1ea910c2-a69c-4b65-a2dd-8570240e8675.

Bandas, J. C., Y. Koldenhof, and T. J. Sellers (2020). “Determining Collision Risks for Fixed Offshore Constructions”. In: *Proceedings of the SNAME Maritime Convention 2020, 29 September - 2 October*.

Bar-Yam, Y. (2002). “General Features of Complex Systems”. In: *Knowledge Management, Organizational Intelligence and Learning, and Complexity*. Vol. 1. Encyclopedia of Life Support Systems.

— (2006). “Engineering Complex Systems: Multiscale Analysis and Evolutionary Engineering”. In: *Complex Engineered Systems. Understanding Complex Systems*. Ed. by D. Braha, A. Minai, and Y. Bar-Yam. Springer, Berlin, Heidelberg.

Barredo Arrieta, A., N. Díaz-Rodríguez, J. Del Ser, A. Bennetot, S. Tabik, A. Barbado, S. Garcia, S. Gil-Lopez, D. Molina, R. Benjamins, R. Chatila, and F. Herrera (2020). “Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI”. In: *Information Fusion* 58, pp. 82–115. ISSN: 1566-2535. DOI: https://doi.org/10.1016/j.inffus.2019.12.012.

Barrios, R. E., C. Lim, M. S. Kelley, and X. Li (2021). “SARS-CoV-2 concentrations in a wastewater collection system indicated potential COVID-19 hotspots at the zip code level”. In: *Science of the Total Environment* 800. DOI: 10.1016/j.scitotenv.2021.149480.

Battista, G. D., H. Kangassalo, and R. Tamassia (1989). “Definition libraries for conceptual modelling”. In: *Data & Knowledge Engineering* 4.3, pp. 245–260. DOI: https://doi.org/10.1016/0169-023X(89)90022-0.

Bedford, T. and R. Cooke (2001). *Probabilistic risk analysis: foundations and methods*. Cambridge University Press.

Bellsolà Olba, X., W. Daamen, T. Vellinga, and S. P. Hoogendoorn (2018). “State-of-the-art of port simulation models for risk and capacity assessment based on the vessel navigational behaviour through the nautical infrastructure”. In: *Journal of Traffic*

and Transportation Engineering (English Edition) 5.5, pp. 335–347. ISSN: 2095-7564. DOI: https://doi.org/10.1016/j.jtte.2018.03.003.
Benchaji, I., S. Douzi, B. El Ouahidi, and J. Jaafari (2021). "Enhanced credit card fraud detection based on attention mechanism and LSTM deep model". In: *Journal of Big Data* 8.1, p. 151. DOI: 10.1186/s40537-021-00541-8.
Biswas, A. K. (1975). "Mathematical modelling and environmental decision-making". In: *Ecological Modelling* 1.1, pp. 31–48. ISSN: 0304-3800. DOI: https://doi.org/10.1016/0304-3800(75)90004-6.
Borau, C., K. Wertheim, S. Hervas-Raluy, D. Sainz-DeMena, D. Walker, R. Chisholm, P. Richmond, V. Varella, M. Viceconti, A. Montero, E. Gregori-Puigjané, J. Mestres, M. Kasztelnik, and J. García-Aznar (2023). "A multiscale orchestrated computational framework to reveal emergent phenomena in neuroblastoma". In: *Computer Methods and Programs in Biomedicine* 241, p. 107742. ISSN: 0169-2607. DOI: https://doi.org/10.1016/j.cmpb.2023.107742.
Botnariuc, L., J. Dahlkamp, J. Diehl, M. Gebauer, H. Gude, R. Höfner, M. Knobbe, R. Lehberger, F. Obermaier, J. Puhl, A. Berlin, M. Rosenbach, F. Schmid, S. Sperber, T. Schröder, T. Schulz, G. Traufetter, W. Wiedmann-Schmidt, and J.-P. Ziegler (2023). "Investigating the Nord Stream Attack - All the Evidence Points To Kyiv". In: *Der Spiegel* 35.
Brax, C. (2011). "Anomaly Detection in the Surveillance Domain". PhD thesis. Örebro University.
Breunig, M. M., H.-P. Kriegel, R. T. Ng, and J. Sander (2000). "LOF: identifying density-based local outliers". In: *SIGMOD Rec.* 29.2, pp. 93–104. DOI: 10.1145/335191.335388.
Bunge, M. A. (1979). *Treatise on Basic Philosophy: Ontology II: A World of Systems*. Reidel Publishing Company.
Calkoen, F. R., A. P. Luijendijk, K. Vos, E. Kras, and F. Baart (2025). "Enabling coastal analytics at planetary scale". In: *Environmental Modelling & Software* 183, p. 106257. DOI: https://doi.org/10.1016/j.envsoft.2024.106257.
Cambridge Academic Content Dictionary (2024). "agent, n." In: *https://dictionary.cambridge.org*. Cambridge University Press.
Cattell, R. B. (1966). "The Scree Test For The Number Of Factors". In: *Multivariate Behavioral Research* 1.2, pp. 245–276. DOI: 10.1207/s15327906mbr0102{_}10.
Chandola, V., A. Banerjee, and V. Kumar (2009). "Anomaly detection: A survey". In: *ACM Computing Surveys* 41.3, pp. 1–58. DOI: 10.1145/1541880.1541882.
Chen, P., Y. Huang, J. Mou, and P. van Gelder (2019). "Probabilistic risk analysis for ship-ship collision: State-of-the-art". In: *Safety Science* 117, pp. 108–122. DOI: https://doi.org/10.1016/j.ssci.2019.04.014.
Christ, M., N. Braun, J. Neuffer, A. Kempa-Liehr, et al. (2025). *tsfresh*. URL: https://github.com/blue-yonder/tsfresh.
Conférence Européenne des Ministres des Transports (1992). *Resolution No. 92/2 on New Classification of Inland Waterways*. Statute. URL: https://www.itf-oecd.org/sites/default/files/docs/wat19922e.pdf.
Cooke, D. L. (2003). "A system dynamics analysis of the Westray mine disaster". In: *System Dynamics Review* 19.2, pp. 139–166. DOI: 10.1002/sdr.268.

Čorić, M., S. Mandžuka, A. Gudelj, and Z. Lušić (2021). “Quantitative Ship Collision Frequency Estimation Models: A Review”. In: *Journal of Marine Science and Engineering* 9.5. DOI: 10.3390/jmse9050533.

Coussement, K. and D. F. Benoit (2021). “Interpretable data science for decision making”. In: *Decision Support Systems* 150. Interpretable Data Science For Decision Making, p. 113664. ISSN: 0167-9236. DOI: https://doi.org/10.1016/j.dss.2021.113664.

Crilly, N. (2024). *Design Thinking and Other Approaches - How Different Disciplines See, Think and Act*. Cambridge University Press & Assessment.

Dagestad, K.-F., J. Röhrs, Ø. Breivik, and B. Ådlandsvik (2018a). “OpenDrift v1.0: a generic framework for trajectory modelling”. In: *Geoscientific Model Development* 11.4, pp. 1405–1420. DOI: 10.5194/gmd-11-1405-2018.

Dagestad, K.-F., johannesro, heleneasb, N. M. Kristensen, T. Kristiansen, paulskeie, and A. R. Brodtkorb. (2018b). *OpenDrift/opendrift: OpenDrift compliant with both Python2 and Python3*. DOI: 10.5194/gmd-11-1405-2018.

Dakic, D., D. Stefanovic, I. Cosic, T. Lolic, and M. Medojevic (2018). “Business Process Mining Application: A Literature Review”. In: *Proceedings of the 29th DAAAM International Symposium on Intelligent Manufacturing and Automation*. Ed. by B. Katalinic. DAAAM International, pp. 0866–0875. DOI: 10.2507/29th.daaam.proceedings.125.

Daranda, A. and G. Dzemyda (2020). “Navigation Decision Support: Discover of Vessel Traffic Anomaly According to the Historic Marine Data”. In: *International Journal of Computers Communications & Control* 15.3, pp. 2127–2144. DOI: 10.15837/ijccc.2020.3.3864.

Dutch Government (2023). Dutch Government, https:data.overheid.nl, (accessed: 23-12-2023 12:35).

de Jong, J., F. Baart, and M. Zagonjolli (2021). *Topological Network of the Dutch Fairway Information System*. Zenodo. DOI: 10.5281/ZENODO.4578289.

de Savigny, D., T. Adam, and S. Mookherji (2009). *Systems Thinking for Health Systems Strengthening*. Tech. rep. World Health Organization. DOI: 10.13140/RG.2.1.4720.4325.

Diva, U., D. K. Dey, and S. Banerjee (2008). “Parametric models for spatially correlated survival data for individuals with multiple cancers”. In: *Statistics in Medicine* 27.12, pp. 2127–2144. DOI: https://doi.org/10.1002/sim.3141.

Do Nascimento, V. D., T. A. O. Alves, C. M. de Farias, and D. L. C. Dutra (2024). “A Hybrid Framework for Maritime Surveillance: Detecting Illegal Activities through Vessel Behaviors and Expert Rules Fusion”. In: *Sensors* 24.17. DOI: 10.3390/s24175623.

Consortium, O. G. (2019). *OGC Implementation Standard: Moving Features Encoding Part I: XML Core*.

Dori, D. and H. Sillitto (2017). “What is a System? An Ontological Framework”. In: *Systems Engineering* 20.3, pp. 207–219. DOI: 10.1002/sys.21383.

Durlik, I., L. Gucma, and T. Miller (2023). “Statistical Model of Ship Delays on the Fairway in Terms of Restrictions Resulting from the Port Regulations: Case Study of Świnoujście-Szczecin Fairway”. In: *Applied Sciences* 13.9. ISSN: 2076-3417. DOI: 10.3390/app13095271.

Dutch Inland Shipping Green Deal (2019). *Green Deal on Maritime and Inland Shipping and Ports*. Bill. URL: https://www.greendeals.nl/sites/default/files/2019-11/GD230%

5C%20Greenf%5C%20Deal%5C%20on%5C%20Maritime%5C%20and%5C%20Inland%5C%20shipping%5C%20and%5C%20Ports.pdf.

Dutch Ministry of Infrastructure and Water Management (2022). *Programma Noordzee 2022-2027*. Tech. rep. Dutch Ministry of Infrastructure and Water Management.

Duursma, A., J. van Doorn, Y. Koldenhof, and J. Valstar (2019). *WIND OP ZEE 2030: Gevolgen voor scheepvaartveiligheid en mogelijk mitigerende maatregelen*. Tech. rep. Maritime Research Institute Netherlands (MARIN) and Royal Haskoning DHV.

Düzgün, H. S. and N. Leveson (2018). "Analysis of soma mine disaster using causal analysis based on systems theory (CAST)". In: *Safety Science* 110, pp. 37–57. DOI: 10.1016/j.ssci.2018.07.028.

Eger, P., T. Mathes, A. Zavarsky, and L. Duester (2023). "Measurement report: Inland ship emissions and their contribution to NOx and ultrafine particle concentrations at the Rhine". In: *Atmospheric Chemistry and Physics* 23.15, pp. 8769–8788. ISSN: 16807316. DOI: 10.5194/acp-23-8769-2023.

Ellis, J., B. Forsman, J. Hüffmeier, and J. Johansson (2008). *Methodology for Assessing Risks to Ship Traffic from Offshore Wind Farms*. Tech. rep. Statens Skeppsprovningsanstalt (SSPA).

Eppenga, S. (2024). "Trajectory prediction for drifting ship allision probability calculations". MA thesis. Delft University of Technology.

European Commission (2019). *The European Green Deal*. Bill. URL: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52019DC0640.

Evers, V., A. Kirkels, and M. Godjevac (2023). "Carbon footprint of hydrogen-powered inland shipping: Impacts and hotspots". In: *Renewable and Sustainable Energy Reviews* 185. ISSN: 13640321. DOI: 10.1016/j.rser.2023.113629.

Fan, A., J. Wang, Y. He, M. Perčić, N. Vladimir, and L. Yang (2021). "Decarbonising inland ship power system: Alternative solution and assessment method". In: *Energy* 226. ISSN: 03605442. DOI: 10.1016/j.energy.2021.120266.

Fan, A., Y. Xiong, L. Yang, H. Zhang, and Y. He (2023). "Carbon footprint model and low–carbon pathway of inland shipping based on micro–macro analysis". In: *Energy* 263. ISSN: 03605442. DOI: 10.1016/j.energy.2022.126150.

Flood, R. C. and M. C. Jackson (1991). "Critical Systems Thinking. Directed Readings". In: *Organization Studies* 14.4, pp. 613–613. DOI: 10.1177/017084069301400416.

Fujii, Y. and R. Shiobara (1971). "The Analysis of Traffic Accidents". In: *Journal of Navigation* 24.4, pp. 534–543. DOI: 10.1017/S0373463300022372.

Gao, D., W. Zhang, A. Shen, and Y. Wang (2017). "Parameter design and energy control of the power train in a hybrid electric boat". In: *Energies* 10.7. ISSN: 19961073. DOI: 10.3390/en10071028.

Gillies, S., C. van der Wel, J. van den Bossche, M. W. Taves, J. Arnott, B. C. Ward, et al. (2022). *Shapely, Manipulation and analysis of geometric objects in the Cartesian plane*. Version 2.0.0. DOI: 10.5281/zenodo.7428463. URL: https://doi.org/10.5281/zenodo.7428463.

Goerlandt, F. and P. Kujala (2014). "On the reliability and validity of ship–ship collision risk analysis in light of different perspectives on risk". In: *Safety Science* 62, pp. 348–365. ISSN: 0925-7535. DOI: https://doi.org/10.1016/j.ssci.2013.09.010.

Goerlandt, F. and J. Montewka (2015). “Maritime transportation risk analysis: Review and analysis in light of some foundational issues”. In: *Reliability Engineering & System Safety* 138, pp. 115–134. ISSN: 0951-8320. DOI: https://doi.org/10.1016/j.ress.2015.01.025.

Goldsworthy, L. and B. Goldsworthy (2015). “Modelling of ship engine exhaust emissions in ports and extensive coastal waters based on terrestrial AIS data - An Australian case study”. In: *Environmental Modelling and Software* 63, pp. 45–60. ISSN: 1364-8152. DOI: 10.1016/J.ENVSOFT.2014.09.009.

Gosiewska, A., A. Kozak, and P. Biecek (2021). “Simpler is better: Lifting interpretability-performance trade-off via automated feature engineering”. In: *Decision Support Systems* 150. Interpretable Data Science For Decision Making, p. 113556. ISSN: 0167-9236. DOI: https://doi.org/10.1016/j.dss.2021.113556.

Graser, A., A. Jalali, J. Lampert, A. Weissenfeld, and K. Janowicz (2024). “MobilityDL: a review of deep learning from trajectory data”. In: *GeoInformatica*. DOI: 10.1007/s10707-024-00518-8.

Guarino, N., G. Guizzardi, and J. Mylopoulos (2019). “On the Philosophical Foundations of Conceptual Models”. In: *29th International Conference on Information Modelling and Knowledge Bases (EJC 2019)*. IOS Press. DOI: 10.3233/FAIA200002.

Gupta, A., G. Poels, and P. Bera (2023). “Generating multiple conceptual models from behavior-driven development scenarios”. In: *Data & Knowledge Engineering* 145, p. 102141. DOI: https://doi.org/10.1016/j.datak.2023.102141.

Haklay, M. and P. Weber (2008). “OpenStreetMap: User-Generated Street Maps”. In: *IEEE Pervasive Computing* 7.4, pp. 12–18. DOI: 10.1109/MPRV.2008.80.

Hall, D., Y. Guo, R. A. Davis, and C. Cegielski (2005). “Extending Unbounded Systems Thinking with agent-oriented modeling: conceptualizing a multiple perspective decision-making support system”. In: *Decision Support Systems* 41.1, pp. 279–295. ISSN: 0167-9236. DOI: https://doi.org/10.1016/j.dss.2004.06.009.

Han, H., W. Li, J. Wang, G. Qin, and X. Qin (2022). “Enhance explainability of manifold learning”. In: *Neurocomputing* 500, pp. 877–895. DOI: https://doi.org/10.1016/j.neucom.2022.05.119.

Hassel, M., I. B. Utne, and J. E. Vinnem (2021). “An allision risk model for passing vessels and offshore oil and gas installations on the Norwegian Continental Shelf”. In: *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability* 235.1, pp. 17–32. DOI: 10.1177/1748006X20957481.

Heino, M. T., S. Bilodeau, G. Fox, C. Gershenson, and Y. Bar-Yam (2023). “Crafting Policies for an Interconnected World”. In: *WHN Science Communications* 4.10, 1:1.

Hekkenberg, R. G., C. van Dorsser, and J. Schweighofer (2017). “Modelling sailing time and cost for inland waterway transport”. In: *European Journal of Transport and Infrastructure Research* 17.4. DOI: 10.18757/ejtir.2017.17.4.3212.

Hekkenberg, R. G. (2013). “Inland ships for efficient transport chains.” PhD thesis. Delft University of Technology. ISBN: 9789461860996. DOI: 10.4233/uuid:f2ead20f-80b5-4d92-818f-7586c7b85f76.

Herman, P. M., A. C. van der Lelij, E. Ieno, M. Leopold, H. Schekkerman, K. Troost, J. Craeymeersch, A. I. Bijleveld, and L. van den Bogaart (2021). *Statistical analysis of* *effects of MSC Zoe incident on populations of protected species in Wadden Sea and North Sea*. Tech. rep. Deltares.

Hersbach, H., B. Bell, P. Berrisford, G. Biavati, A. Horányi, J. Muñoz Sabater, J. Nicolas, C. Peubey, R. Radu, I. Rozum, D. Schepers, A. Simmons, C. Soci, D. Dee, and J.-N. Thépaut (2023). *ERA5 hourly data on single levels from 1940 to present. Copernicus Climate Change Service (C3S) Climate Data Store (CDS)*. Accessed on 16-06-2024. DOI: 10.24381/cds.adbb2d47.

Hofman, M. and V. Kozarski (2000). "Shallow Water Resistance Charts for Preliminary Vessel Design". In: *International Shipbuilding Progress* 47.449, pp. 61–76.

Holtrop, J. and G. Mennen (1978). "A statistical Power Prediction Method". In: *International shipbuilding progress* 25.290, pp. 253–256.

Hossain, M. P., W. Zhou, M. Y. T. Leung, and H.-Y. Yuan (2024). "Association of air pollution and weather conditions during infection course with COVID-19 case fatality rate in the United Kingdom". In: *Scientific Reports* 14.1, p. 683. DOI: 10.1038/s41598-023-50474-w.

IV-Infra (2025). *3D FEM Analysis of the Effects of a Ship Collision on a Wind Turbine Support Structure*. Tech. rep. INFR240476-R203-DP5. Trapezium 322, 3364 DL Sliedrecht, The Netherlands: IV-Infra B.V. URL: https://www.noordzeeloket.nl/publish/pages/239195/3d-fem-analysis-of-the-effects-of-a-ship-collission-on-a-wind-turbine-support-structure_1.pdf.

Islam, A., M. A. Sayeed, M. K. Rahman, J. Ferdous, S. Islam, and M. M. Hassan (2021). "Geospatial dynamics of COVID-19 clusters and hotspots in Bangladesh". In: *Transboundary and Emerging Diseases* 68.6, pp. 3643–3657. DOI: 10.1111/tbed.13973.

Jackson, P. (2006). "Thinking Geographically". In: *Geography* 91.3, pp. 199–204. DOI: 10.1080/00167487.2006.12094167.

Jalkanen, J.-P., L. Johansson, J. Kukkonen, A. Brink, J. Kalli, and T. Stipa (2012). "Extension of an assessment model of ship traffic exhaust emissions for particulate matter and carbon monoxide". In: *Atmospheric Chemistry and Physics* 12 (5), pp. 2641–2659. ISSN: 1680-7324. DOI: 10.5194/acp-12-2641-2012. URL: https://acp.copernicus.org/articles/12/2641/2012/.

Jiang, H., D. Peng, Y. Wang, and M. Fu (2021). "Comparison of inland ship emission results from a real-world test and an ais-based model". In: *Atmosphere* 12.12. ISSN: 20734433. DOI: 10.3390/atmos12121611.

Jiang, M., L. Segers, S. van der Werff, F. Baart, and M. van Koningsveld (2022). *OpenTNSim*. Software. DOI: 10.5281/ZENODO.6390276. URL: https://zenodo.org/record/6390276.

Jiang, M., F. Baart, K. Visser, R. Hekkenberg, and M. van Koningsveld (2023). "Corridor Scale Planning of Bunker Infrastructure for Zero-Emission Energy Sources in Inland Waterway Transport". In: *Proceedings of PIANC Smart Rivers 2022*. Ed. by Y. Li, Y. Hu, P. Rigo, F. E. Lefler, and G. Zhao. Springer Nature Singapore, pp. 334–345. DOI: https://doi.org/10.1007/978-981-19-6138-0_30.

Johansson, M. A., H. Wolford, P. Paul, P. S. Diaz, T.-H. Chen, C. M. Brown, M. S. Cetron, and F. Alvarado-Ramy (2021). "Reducing travel-related SARS-CoV-2 transmission with layered mitigation measures: symptom monitoring, quarantine, and testing". In: *BMC Medicine* 325, p. 94. ISSN: 1741-7015. DOI: https://doi.org/10.1186/s12916-021-01975-w.

Minister of Infrastructure and Water Management (2020a). Kamerstukken II, 31409, nr. 307, 2020.
Kanter, J. M. and K. Veeramachaneni (2015). “Deep feature synthesis: Towards automating data science endeavors”. In: *2015 IEEE International Conference on Data Science and Advanced Analytics (DSAA)*, pp. 1–10. DOI: 10.1109/DSAA.2015.7344858.
Kaplan, S. and B. J. Garrick (1981). “On The Quantitative Definition of Risk”. In: *Risk Analysis* 1.1, pp. 11–27. DOI: https://doi.org/10.1111/j.1539-6924.1981.tb01350.x.
Kauranen, A. (2025). “Oil tanker sabotage crew were poised to cut more cables when caught, Finland says”. In: *Reuters*. URL: https://www.reuters.com/world/europe/oil-tanker-sabotage-crew-were-poised-cut-more-cables-when-caught-finland-says-2025-01-13/.
Kazemi, S., S. Abghari, N. Lavesson, H. Johnson, and P. Ryman (2013). “Open data for anomaly detection in maritime surveillance”. In: *Expert Systems with Applications* 40.14, pp. 5719–5729. DOI: https://doi.org/10.1016/j.eswa.2013.04.029.
Kennis- en Exploitatiecentrum Officiële Overheidspublicaties (KOOP) (2024). *Data Register of the Dutch Government*. Dutch Government, https://data.overheid.nl, (accessed: 30-01-2024).
Keuken, M. P., M. Moerman, J. Jonkers, J. Hulskotte, H. Denier van der Gon, G. Hoek, and R. S. Sokhi (2014). “Impact of inland shipping emissions on elemental carbon concentrations near waterways in The Netherlands”. In: *Atmospheric Environment* 95, pp. 1–9. ISSN: 1352-2310. DOI: 10.1016/J.ATMOSENV.2014.06.008.
Kianfar, N. and M. S. Mesgari (2022). “GIS-based spatio-temporal analysis and modeling of COVID-19 incidence rates in Europe”. In: *Spatial and Spatio-temporal Epidemiology* 41. DOI: 10.1016/j.sste.2022.100498.
Kim, S. J., J. K. Seo, K. Y. Ma, and J. S. Park (2021). “Methodology for collision-frequency analysis of wind-turbine installation vessels”. In: *Ships and Offshore Structures* 16.4, pp. 423–439. DOI: 10.1080/17445302.2020.1735835.
Klir, G. J. (1985). “Complexity: Some general observations”. In: *Systems Research* 2.2, pp. 131–140. DOI: https://doi.org/10.1002/sres.3850020205.
Koedijk, O. (2020). *Richtlijnen Vaarwegen 2020*. Standard. Rijkswaterstaat. URL: https://standaarden.rws.nl/link/standaard/994.
Koldenhof, Y., H. Nijsse, C. van der Tak, and C. Glansdorp (2010). “Risk analysis as an integrated operational and legal instrument with respect to the safety of maritime traffic”. In: *WIT Transactions on Information and Communication Technologies* 43, pp. 245–256.
Kolkman, M., M. Kok, and A. van der Veen (2005). “Mental model mapping as a new tool to analyse the use of information in decision-making in integrated water management”. In: *Physics and Chemistry of the Earth, Parts A/B/C* 30.4, pp. 317–332. ISSN: 1474-7065. DOI: https://doi.org/10.1016/j.pce.2005.01.002.
Kontovas, C. A. and H. N. Psaraftis (2009). “Formal Safety Assessment: A Critical Review”. In: *Marine Technology and SNAME News* 46.01, pp. 45–59. ISSN: 0025-3316. DOI: 10.5957/mtsn.2009.46.1.45.
Krause, K., F. Wittrock, A. Richter, D. Busch, A. Bergen, J. P. Burrows, S. Freitag, and O. Halbherr (2023). “Determination of NOx emission rates of inland ships from on-

shore measurements”. In: *Atmospheric Measurement Techniques* 16.7, pp. 1767–1787. ISSN: 18671381. DOI: 10.5194/amt-16-1767-2023.

Krüger, S. and L. Jannsen (2020). *Investigation into the Container loss of the Container Vessel MSC Zoe in the North Sea on 01 and 02 January 2019*. Tech. rep. Institut für Entwerfen von Schiffen und Schiffssicherheit, Technische Universität Hamburg.

Kuiper, F. (2023). “Understanding the locking process using vessel tracking data”. MA thesis. Delft University of Technology. URL: http://resolver.tudelft.nl/uuid:e557197a-5056-4fdd-9aa4-7ccd23edb3c5.

Kurtenbach, R., K. Vaupel, J. Kleffmann, U. Klenk, E. Schmidt, and P. Wiesen (2016). “Emissions of NO, NO2 and PM from inland shipping”. In: *Atmospheric Chemistry and Physics* 16.22, pp. 14285–14295. ISSN: 16807316. DOI: 10.5194/acp-16-14285-2016.

Lane, R., D. Nevell, S. Hayward, and T. Beaney (2010). “Maritime anomaly detection and threat assessment”. In: *13th Conference on Information Fusion, Fusion 2010*, pp. 1–8. DOI: 10.1109/icif.2010.5711998.

Laxhammar, R. and G. Falkman (2015). “Inductive conformal anomaly detection for sequential detection of anomalous sub-trajectories”. In: *Annals of Mathematics and Artificial Intelligence* 74.1, pp. 67–94.

Li, C.-H., L.-L. Chen, L.-B. Yang, and W.-B. Peng (2021). “Analysis on Collapse Accident of Dongjiang Bridge in Heyuan, Guangdong Province”. In: *Zhongguo Gonglu Xuebao/China Journal of Highway and Transport* 34.2, pp. 211–219. DOI: 10.19721/j.cnki.1001-7372.2021.02.010.

Li, S., S. Bao, C. Yao, and L. Zhang (2022). “Exploring the Spatio-Temporal and Behavioural Variations in Taxi Travel Based on Big Data during the COVID-19 Pandemic: A Case Study of New York City”. In: *Sustainability (Switzerland)* 14.20. DOI: 10.3390/su142013548.

Ligterink, N., R. van Gijswijk, G. Kadijk, R. Vermeulen, A. Indrajuana, and M. Elstgeest (2019). *Emissiefactoren wegverkeer - Actualisatie 2019*. Tech. rep. 2019-STL-RAP-100321751. Anna van Buerenplein 1, 2529 DA Den Haag: TNO.

Lukyanenko, R., V. C. Storey, and O. Pastor (2022). “System: A core conceptual modeling construct for capturing complexity”. In: *Data & Knowledge Engineering* 141, p. 102062. DOI: 10.1016/j.datak.2022.102062.

Luo, X., R. Yan, and S. Wang (2024). “Ship sailing speed optimization considering dynamic meteorological conditions”. In: *Transportation Research Part C: Emerging Technologies* 167, p. 104827. ISSN: 0968-090X. DOI: https://doi.org/10.1016/j.trc.2024.104827.

Mans, R. S., M. H. Schonenberg, M. Song, W. M. P. van der Aalst, and P. J. M. Bakker (2009). “Application of Process Mining in Healthcare – A Case Study in a Dutch Hospital”. In: *Biomedical Engineering Systems and Technologies*. Ed. by A. Fred, J. Filipe, and H. Gamboa. Springer Berlin Heidelberg, pp. 425–438. DOI: 10.1007/978-3-540-92219-3_32.

Marine Environment Protection Committee (2018). *RESOLUTION MEPC.304(72) - Adoption of the Initial IMO Strategy on Reduction of GHG Emissions from Ships*. Resolution. URL: https://wwwcdn.imo.org/localresources/en/KnowledgeCentre/IndexofIMOResolutions/MEPCDocuments/MEPC.304(72).pdf.

Marine Safety Investigation Unit (2022). *Marine Safety Investigation Report No. 02/2023*. Tech. rep. 027. Marine Safety Investigation Unit, Transport Malta.
Maritime Safety Committee (1998). *RESOLUTION MSC.74(69)*. Resolution. URL: https://wwwcdn.imo.org/localresources/en/KnowledgeCentre/IndexofIMOResolutions/MSCResolutions/MSC.74(69).pdf.
Marsh, H. W., O. Lüdtke, B. Muthén, T. Asparouhov, A. J. Morin, U. Trautwein, and B. Nagengast (2010). "A new look at the big five factor structure through exploratory structural equation modeling." In: *Psychological assessment* 22.3, p. 471.
McInnes, L., J. Healy, and J. Melville (2020). *UMAP: Uniform Manifold Approximation and Projection for Dimension Reduction*. arXiv: 1802.03426 [stat.ML]. URL: https://arxiv.org/abs/1802.03426.
Microsoft Open Source, M. McFarland, R. Emanuele, D. Morris, and T. Augspurger (2022). *microsoft/PlanetaryComputer: October 2022*. DOI: 10.5281/ZENODO.7261897.
Minister of Infrastructure and Water Management (2020b). *Beleidskader maritieme veiligheid: In Veilige Vaart Vooruit*. Tech. rep. Dutch Ministry of Infrastructure and Water Management.
— (2022). *Subsidieverlening Zero Emission Services, aanleg laadstations en aanschaf energiecontainers*. Decree. URL: https://www.rijksoverheid.nl/documenten/besluiten/2022/12/02/subsidiebesluit-project-zero-emissie-binnenvaart.
Mitroff, I. I., F. Betz, L. R. Pondy, and F. Sagasti (1974). "On Managing Science in the Systems Age: Two Schemas for the Study of Science as a Whole Systems Phenomenon". In: *Interfaces* 4 (3), pp. 45–60. ISSN: 1526-551X. DOI: 10.1287/inte.4.3.46.
Mitroff, I. and H. Linstone (1993). *The Unbounded Mind: Breaking the Chains of Traditional Business Thinking*. Oxford Univ. Press.
Mokbel, M., M. Sakr, L. Xiong, A. Züfle, J. Almeida, T. Anderson, W. Aref, G. Andrienko, N. Andrienko, Y. Cao, S. Chawla, R. Cheng, P. Chrysanthis, X. Fei, G. Ghinita, A. Graser, D. Gunopulos, C. S. Jensen, J.-S. Kim, K.-S. Kim, P. Kröger, J. Krumm, J. Lauer, A. Magdy, M. Nascimento, S. Ravada, M. Renz, D. Sacharidis, F. Salim, M. Sarwat, M. Schoemans, C. Shahabi, B. Speckmann, E. Tanin, X. Teng, Y. Theodoridis, K. Torp, G. Trajcevski, M. van Kreveld, C. Wenk, M. Werner, R. Wong, S. Wu, J. Xu, M. Youssef, D. Zeinalipour, M. Zhang, and E. Zimányi (2024). "Mobility Data Science: Perspectives and Challenges". In: *ACM Trans. Spatial Algorithms Syst.* 10.2. ISSN: 2374-0353. DOI: 10.1145/3652158.
Narayan, A., B. Berger, and H. Cho (2021). "Assessing single-cell transcriptomic variability through density-preserving data visualization". In: *Nature Biotechnology* 39.6, pp. 765–774. DOI: 10.1038/s41587-020-00801-7.
Ngonghala, C. N., E. Iboi, S. Eikenberry, M. Scotch, C. R. MacIntyre, M. H. Bonds, and A. B. Gumel (2020). "Mathematical assessment of the impact of non-pharmaceutical interventions on curtailing the 2019 novel Coronavirus". In: *Mathematical Biosciences* 325, p. 108364. ISSN: 0025-5564. DOI: https://doi.org/10.1016/j.mbs.2020.108364.
Noll, V. H. (1935). "Measuring the scientific attitude." In: *The Journal of Abnormal and Social Psychology* 30.2, p. 145.
Nourali, Z., J. E. Shortridge, A. Bukvic, Y. Shao, and J. L. Irish (2024). "Simulation of Flood-Induced Human Migration at the Municipal Scale: A Stochastic Agent-Based

Model of Relocation Response to Coastal Flooding”. In: *Water* 16.2. ISSN: 2073-4441. DOI: 10.3390/w16020263.

Pallotta, G. and A.-L. Jousselme (2015). “Data-driven detection and context-based classification of maritime anomalies”. In: *2015 18th International Conference on Information Fusion (Fusion)*, pp. 1152–1159.

Panchal, Y., R. Sheikh, K. K. Sethi, P. K. Bhanodia, S. S. Rajput, and N. P. S. Rathore (2024). “Privacy Preserving Techniques in Data Science : A Review”. In: *2024 International Conference on Advances in Computing Research on Science Engineering and Technology (ACROSET)*. DOI: 10.1109/ACROSET62108.2024.10743362.

Parvin, F., S. A. Ali, S. N. I. Hashmi, and A. Ahmad (2021). “Spatial prediction and mapping of the COVID-19 hotspot in India using geostatistical technique”. In: *Spatial Information Research* 29, pp. 479–494. DOI: 10.1007/s41324-020-00375-1.

Pedregosa, F., G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and É. Duchesnay (2011). “Scikit-learn: Machine learning in Python”. In: *Journal of Machine Learning Research* 12, pp. 2825–2830.

PIANC-InCom-WG229 (2024). *Guideline for Air Pollutants and Carbon Emissions Performance Indicators for Inland Waterways*. Report. PIANC InCom. URL: https://www.pianc.org/publication/guidelines-for-air-pollutants-and-carbon-emissions-performance-indicators-for-inland-waterways/.

PIANC-InCom-WG234 (2023). *Infrastructure for the decarbonisation of IWT*. Report. PIANC InCom. URL: https://www.pianc.org/publication/infrastructure-for-the-decarbonisation-of-inland-waterway-transport/.

Port of Rotterdam (2023). Partners launch Condor H2 for emission-free inland and near-shore shipping, https://www.portofrotterdam.com/en/news-and-press-releases/whs2023-partners-launch-condor-h2-for-emission-free-inland-and-near-shore, (accessed: 2024-06-20).

Pratson, L. F. (2023). “Assessing impacts to maritime shipping from marine chokepoint closures”. In: *Communications in Transportation Research* 3, p. 100083. ISSN: 2772-4247. DOI: https://doi.org/10.1016/j.commtr.2022.100083.

Purwanto, P., S. Utaya, B. Handoyo, S. Bachri, I. S. Astuti, K. S. B. Utomo, and Y. E. Aldianto (2021). “Spatiotemporal Analysis of COVID-19 Spread with Emerging Hotspot Analysis and Space–Time Cube Models in East Java, Indonesia”. In: *ISPRS International Journal of Geo-Information* 10.3. ISSN: 2220-9964. DOI: 10.3390/ijgi10030133.

Queen, C. M. and C. J. Albers (2009). “Intervention and causality: Forecasting traffic flows using a dynamic bayesian network”. In: *Journal of the American Statistical Association* 104.486, pp. 669–681. DOI: 10.1198/jasa.2009.0042.

Radon, A. N., K. Wang, U. Glässer, H. Wehn, and A. Westwell-Roper (2015). “Contextual verification for false alarm reduction in maritime anomaly detection”. In: *2015 IEEE International Conference on Big Data (Big Data)*, pp. 1123–1133. DOI: 10.1109/BigData.2015.7363866.

Randall, A. (2011). *Risk and Precaution*. Cambridge University Press. ISBN: 9781139494793.

Rao, M. (1971). “Cluster analysis and mathematical programming”. In: *Journal of the American statistical association* 66.335, pp. 622–626.

Rawson, A. and M. Brito (2022). “Assessing the validity of navigation risk assessments: A study of offshore wind farms in the UK”. In: *Ocean & Coastal Management* 219, p. 106078. ISSN: 0964-5691. DOI: https://doi.org/10.1016/j.ocecoaman.2022.106078.

Ribeiro, C. V., A. Paes, and D. de Oliveira (2023). “AIS-based maritime anomaly traffic detection: A review”. In: *Expert Systems with Applications* 231, p. 120561. DOI: https://doi.org/10.1016/j.eswa.2023.120561.

Rijkswaterstaat (2024a). *Geoviewer SOS-database with Shipping Accidents on Dutch Inland Waterways*. Rijkswaterstaat, https://maps.rijkswaterstaat.nl/gwproj55/index.html?viewer=Scheepsongevallen_Openbaar.Webviewer, (accessed: 29-01-2025 20:07).

— (2024b). *Fairways and Infrastructure Netherlands*. Rijkswaterstaat, https://www.vaarweginformatie.nl, (accessed: 2024-06-20).

Riveiro, M., G. Pallotta, and M. Vespe (2018). “Maritime anomaly detection: A review”. In: *WIREs Data Mining and Knowledge Discovery* 8.5, e1266. DOI: https://doi.org/10.1002/widm.1266.

Rocklin, M. (2015). “Dask: Parallel computation with blocked algorithms and task scheduling”. In: *Proceedings of the 14th Python in Science Conference (SciPy 2015)*, pp. 126–132.

Rong, H., A. Teixeira, and C. Guedes Soares (2024). “A framework for ship abnormal behaviour detection and classification using AIS data”. In: *Reliability Engineering & System Safety* 247, p. 110105. DOI: https://doi.org/10.1016/j.ress.2024.110105.

Roy, J. (2010). “Rule-based expert system for maritime anomaly detection”. In: *Sensors, and Command, Control, Communications, and Intelligence (C3I) Technologies for Homeland Security and Homeland Defense IX*. Ed. by E. M. Carapezza. Vol. 7666. International Society for Optics and Photonics. SPIE, 76662N. DOI: 10.1117/12.849131.

Russon, M.-A. (2021). *The cost of the Suez Canal blockage*. BBC News, https://www.bbc.com/news/business-56559073, (accessed: 01-10-2024 09:54).

Sarasvathy, S. D. (2008). “Effectuation: Elements of entrepreneurial expertise”. In: *Effectuation*. Edward Elgar Publishing.

Segers, L. (2021). “Mapping inland shipping emissions in time and space for the benefit of emission policy development”. MA thesis. Stevinweg 1, 2628 CN Delft: Delft University of Technology. URL: https://repository.tudelft.nl/islandora/object/uuid%5C%3Aa260bc48-c6ce-4f7c-b14a-e681d2e528e3.

Senge, P. (1997). *The Fifth Discipline: The art and practice of the learning organization*. Doubleday.

Sidibé, A. and G. Shu (2017). “Study of Automatic Anomalous Behaviour Detection Techniques for Maritime Vessels”. In: *Journal of Navigation* 70.4, pp. 847–858. DOI: 10.1017/S0373463317000066.

Siegenfeld, A. F. and Y. Bar-Yam (2020). “An Introduction to Complex Systems Science and Its Applications”. In: *Complexity* 2020, p. 6105872. DOI: 10.1155/2020/6105872.

Siew, T. (2008). “Connecting Science and Decision-making: A Conceptual Framework through Organisation Knowledge Management”. In: *Proceedings of the 4th Biennual International Congress on Environmental Modelling and Software*.

Šimenc, M. (2016). “Overview and comparative analysis of emission calculators for inland shipping”. In: *International Journal of Sustainable Transportation* 10.7, pp. 627–637. ISSN: 15568318. DOI: 10.1080/15568318.2015.1079753.

Singer Jr, E. A. (1959). *Experience and reflection*. University of Pennsylvania Press.
Skyttner, L. (2001). *General Systems Theory, Ideas And Applications*. World Scientific Publishing Company.
Smyth, D. and P. Checkland (1976). “Using a Systems Approach: The Structure of Root Definitions”. In: *Journal of Applied Systems Analysis* 5, pp. 75–83.
Sorel, M., P.-E. Gay, C. Vernier, S. Cissé, and C. Piou (2024). “Upwind flight partially explains the migratory routes of locust swarms”. In: *Ecological Modelling* 489, p. 110622. ISSN: 0304-3800. DOI: https://doi.org/10.1016/j.ecolmodel.2024.110622.
Sørgård, E. and T. Vada (2011). *Observations and modelling of drifting ships*. Tech. rep. Report 96-2011, Tech. rep., 64 pp. DnV.
Spouge, J. R. (1991). “CRASH: Computerised Prediction of Ship-Platform Collision Risks”. In: *Proceedings of SPE Offshore Europe, Aberdeen, United Kingdom, September 1991*. Vol. All Days. SPE Offshore Europe Conference and Exhibition, SPE-23154–MS. DOI: 10.2118/23154-MS.
Tabera Tsilefa, S. and A. Raherinirina (2024). “Spatial Markov matrices for measuring the spatial dependencies of an epidemiological spread : case Covid’19 Madagascar”. In: *BMC Public Health* 24.1, p. 2243. DOI: 10.1186/s12889-024-19654-9.
Tan, Z., X. Zeng, S. Shao, J. Chen, and H. Wang (2022). “Scrubber installation and green fuel for inland river ships with non-identical streamflow”. In: *Transportation Research Part E: Logistics and Transportation Review* 161. ISSN: 13665545. DOI: 10.1016/j.tre.2022.102677.
Tao, F., J. Wu, S. Lin, Y. Lv, Y. Wang, and T. Zhou (2023). “Revealing the Impact of COVID-19 on Urban Residential Travel Structure Based on Floating Car Trajectory Data: A Case Study of Nantong, China”. In: *ISPRS International Journal of Geo-Information* 12.2. DOI: 10.3390/ijgi12020055.
Terwisga, T. (1989). *Weerstand en voortstuwing van bakken: een literatuurstudie*. Tech. rep. 49199-1-RD. Haagsteeg 2, 6708 PM Wageningen: Maritiem Research Instituut Nederland.
Tijdeman, D. (2024). “Exploring the potential of Machine Learning methods to predict energy consumption in shipping”. MA thesis. Delft University of Technology. URL: https://resolver.tudelft.nl/uuid:fa103d5a-fc0d-484e-a8ba-e38999b0bbd7.
Topuz, K. and D. Delen (2021). “A probabilistic Bayesian inference model to investigate injury severity in automobile crashes”. In: *Decision Support Systems* 150. Interpretable Data Science For Decision Making, p. 113557. ISSN: 0167-9236. DOI: https://doi.org/10.1016/j.dss.2021.113557.
Tu, E., G. Zhang, L. Rachmawati, E. Rajabally, and G.-B. Huang (2018). “Exploiting AIS Data for Intelligent Maritime Navigation: A Comprehensive Survey from Data to Methodology”. In: *IEEE Transactions on Intelligent Transportation Systems* 19.5, pp. 1559–1582. DOI: 10.1109/TITS.2017.2724551.
Ahlander, J., E. Lehto, and A. Sytas (2023). Reuters, https://www.reuters.com/business/media-telecom/telecoms-cable-linking-finland-germany-likely-severed-owner-says-2024-11-18/, (accessed: 2024-11-20 13:50).
Umar, A., S. van Hijum, L. van der Veen, L. Sluijs, E. de Vilder, P. Verhallen, M. van Helden, R. de Wit, M. Verschoor, E. Willeboordse, N. Wierda, and S. Lalmohamed

(2020). *Safe Container Transport North of the Wadden Islands - Lessons learned following the loss of containers from MSC Zoe*. Tech. rep. Dutch Safety Board.

Umar, A., L. van der Veen, N. Wierda, M. Rustenburg, C. Reurings, H. Tabak, A. van Delden, and J. Timmermans (2024). *Compromise on Room to Manoeuvre - Managing the safety of shipping in an increasingly crowded North Sea*. Tech. rep. Dutch Safety Board. URL: https://onderzoeksraad.nl/en/onderzoek/intensified-use-north-sea/.

United Nations / Framework Convention on Climate Change (2015). "Adoption of the Paris Agreement". In: *21st Conference of the Parties*. United Nations, UNTC XXVII 7.d.

van den Heuvel, J. (2024). "Improving maritime safety at the North Sea by anomaly detection". MA thesis. Delft University of Technology.

van den Hoek, A. and R. van der Mark (2025). *Vergelijking KNMI'23 en KNMI'14 scenario's ten behoeve van stresstesten KBN-HVWN*. Tech. rep. 11210314-000-ZWS-0001. Boussinesqweg 1, 2629 HV Delft, The Netherlands: Deltares. URL: https://open.rijkswaterstaat.nl/open-overheid/@274307/vergelijking-knmi-23-knmi-14-scenario/.

van der Aalst, W. (2012). "Process Mining". In: *ACM Transactions on Management Information Systems* 3 (2), pp. 1–17. ISSN: 2158-656X. DOI: 10.1145/2229156.2229157.

van der Aalst, W., H. Reijers, A. Weijters, B. van Dongen, A. Alves de Medeiros, M. Song, and H. Verbeek (2007). "Business process mining: An industrial application". In: *Information Systems* 32 (5), pp. 713–732. ISSN: 03064379. DOI: 10.1016/j.is.2006.05.003.

van der Aalst, W., B. van Dongen, J. Herbst, L. Maruster, G. Schimm, and A. Weijters (2003). "Workflow mining: A survey of issues and approaches". In: *Data and Knowledge Engineering* 47 (2), pp. 237–267. ISSN: 0169023X. DOI: 10.1016/S0169-023X(03)00066-1.

van der Molen, J., S. M. van Leeuwen, L. L. Govers, T. van der Heide, and H. Olff (2021). "Potential micro-plastics dispersal and accumulation in the North Sea, with application to the MSC Zoe incident". In: *Frontiers in Marine Science* 8, p. 607203.

van der Werff, S., M. van Koningsveld, and F. Baart (2024). "Vessel Behaviour under Varying Environmental Conditions in Coastal Areas". In: *35th PIANC World Congress 2024: Future Ready Waterborne Transport–Unlocking Africa*. PIANC, pp. 1238–1243.

van Engelen, B. (2023). "Nautical safety on Dutch inland waterways, a study to detect anomalous vessel behaviour based on AIS data". MA thesis. Delft University of Technology.

van Koningsveld, M., S. van der Werff, M. Jiang, J. Lansen, and H. de Vriend (2023). "Performance of Ports and Waterway Systems". In: *Ports and Waterways - Navigating the changing world*. TU Delft Open. DOI: 10.5074/T.2021.004.

Venskus, J., P. Treigys, J. Bernatavičienė, G. Tamulevičius, and V. Medvedev (2019). "Real-Time Maritime Traffic Anomaly Detection Based on Sensors and History Data Embedding". In: *Sensors* 19.17. DOI: 10.3390/s19173782.

Vinke, F., B. Turpijn, P. Gelder, and M. Koningsveld (2024). "Inland shipping response to discharge extremes – A 10 years case study of the Rhine". In: *Climate Risk Management* 43, p. 100578. DOI: https://doi.org/10.1016/j.crm.2023.100578.

Vinke, F., M. van Koningsveld, C. van Dorsser, F. Baart, P. van Gelder, and T. Vellinga (2022). "Cascading effects of sustained low water on inland shipping". In: *Climate*

Risk Management 35, p. 100400. ISSN: 2212-0963. DOI: https://doi.org/10.1016/j.crm.2022.100400.
Von Bertalanffy, L. (1968). *General System Theory: Foundations, Development, Applications*. Braziller.
Vreugdenhil, J. (2013). *Monitoring Nautische Veiligheid 2013*. Tech. rep. Movares.
Weinberg, G. (1975). *An Introduction to General Systems Thinking*. Wiley Series on Systems Engineering and Analysis. Wiley. ISBN: 9780471925637.
Widyantara, I. M. O., I. P. N. Hartawan, A. A. I. N. E. Karyawati, N. I. Er, and K. B. Artana (2023). "Automatic identification system-based trajectory clustering framework to identify vessel movement pattern". In: *IAES International Journal of Artificial Intelligence* 12.1, pp. 1–11. DOI: 10.11591/ijai.v12.i1.pp1-11.
Wilson, J. M. (2003). "Gantt charts: A centenary appreciation". In: *European Journal of Operational Research* 149.2, pp. 430–437. DOI: https://doi.org/10.1016/S0377-2217(02)00769-5.
Wolkenhauer, O., C. Auffray, O. Brass, J. Clairambault, A. Deutsch, D. Drasdo, F. Gervasio, L. Preziosi, P. Maini, A. Marciniak-Czochra, C. Kossow, L. Kuepfer, K. Rateitschak, I. Ramis-Conde, B. Ribba, A. Schuppert, R. Smallwood, G. Stamatakos, F. Winter, and H. Byrne (2014). "Enabling multiscale modeling in systems medicine". In: *Genome Medicine* 6.3, p. 21. DOI: 10.1186/gm538.
Xiao, F., Y. Ma, and B. Wu (2022). "Review of Probabilistic Risk Assessment Models for Ship Collisions with Structures". In: *Applied Sciences* 12.7. DOI: 10.3390/app12073441.
Yang, Z., H. Haeri, and K. Jerath (2021). "Renormalization Group Approach to Cellular Automata-Based Multi-scale Modeling of Traffic Flow". In: *Unifying Themes in Complex Systems X*. Ed. by D. Braha, M. de Aguiar, C. Gershenson, A. J. Morales, L. Kaufman, E. Naumova, A. Minai, and Y. Bar-Yam. International Conference on Complex Systems. Springer Nature Switserland, pp. 17–28.
Zeng, Q., C. Thill, R. Hekkenberg, and E. Rotteveel (2019). "A modification of the ITTC57 correlation line for shallow water". In: *Journal of Marine Science and Technology* 24.2, pp. 642–657. DOI: 10.1007/s00773-018-0578-7. URL: https://doi.org/10.1007/s00773-018-0578-7.
Zhang, R., Y. Li, A. L. Zhang, Y. Wang, and M. J. Molina (2020). "Identifying airborne transmission as the dominant route for the spread of COVID-19". In: *Proceedings of the National Academy of Sciences* 117.26, pp. 14857–14863. DOI: 10.1073/pnas.2009637117.
Zhang, Y., L. Sun, T. Fan, F. Ma, and Y. Xiong (2023). "Speed and energy optimization method for the inland all-electric ship in battery-swapping mode". In: *Ocean Engineering* 284. ISSN: 00298018. DOI: 10.1016/j.oceaneng.2023.115234. URL: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85164314095&doi=10.1016%2fj.oceaneng.2023.115234&partnerID=40&md5=402fe7c4c9a40309ee11486b2957ddb2.
Zhao-Yu Song Prem Chhetri, G. Y. and P. T.-W. Lee (2023). "Green maritime logistics coalition by green shipping corridors: a new paradigm for the decarbonisation of the maritime industry". In: *International Journal of Logistics Research and Applications* 0.0, pp. 1–17. DOI: 10.1080/13675567.2023.2256243.

Curriculum Vitæ

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Professional Experience

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List of Publications

1. **S. van der Werff, F. Baart, and M. van Koningsveld**, *Merging Multiple System Perspectives: the Key to Effective Inland Shipping Emission-Reduction Policy Design*, Journal of Marine Science and Engineering **13**(4), 716 (2025).

2. **S. van der Werff, S. Eppenga, A. van der Hout, P. van Gelder, and M. van Koningsveld**, *Multi-Perspective Nautical Safety Risk Assessment of Allisions with Offshore Wind Parks*, Applied Ocean Research **158**, 104564 (2025).

3. **S. van der Werff, P. van Gelder, F. Baart, and M. van Koningsveld**, *Overarching Domain Perspectives for Agent-Based Systems*, Under review with Data & Knowledge Engineering (2025).

4. **S. van der Werff, F. Baart, and M. van Koningsveld**, *Vessel Behaviour under Varying Environmental Conditions in Coastal Areas*, 35th PIANC World Congress, 29 April – 3 May 2024, Cape Town, South-Africa (2024).

5. **S. van der Werff, F. Baart, and M. van Koningsveld**, *Zoomed-Out Corridor-Level Shipping Emissions, Zoomed-In Ship-Level Causes, and Everything in between*, 35th PIANC World Congress, 29 April – 3 May 2024, Cape Town, South-Africa (2024).

6. **A. Sepehri, A. Kirichek, S. van der Werff, F. Baart, M. van den Heuvel, M. van Koningsveld**, *Analyzing the interaction between maintenance dredging and seagoing vessels: a case study in the Port of Rotterdam*, Journal of Soils and Sediments **24**, 3898–3908 (2024).

7. **F. Bakker, S. van der Werff, F. Baart, A. Kirichek, S. de Jong, M. van Koningsveld**, *Port Accessibility Depends on Cascading Interactions between Fleets, Policies, Infrastructure, and Hydrodynamics*, Journal of Marine Science and Engineering **12(6)**, 1006 (2024).

8. **M. van Koningsveld, A. van der Hout, F. Vinke, S. van der Werff**, *Waterways and Water Bodies*, Ports and Waterways: Navigating the Changing World, Delft University of Technology (2021).

9. **M. van Koningsveld, S. van der Werff, M. Jiang, A. Lansen**, *Performance of Ports and Waterway Systems*, Ports and Waterways: Navigating the Changing World, Delft University of Technology (2021).