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Doctoral thesis

**NTNU**
Norwegian University of Science and Technology
Thesis for the Degree of Philosophiae Doctor
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# Preface

This thesis is submitted in partial fulfilment of the requirements for the degree of Philosophiae Doctor (PhD) at the Department of Engineering Cybernetics at the Norwegian University of Science and Technology (NTNU) in Norway. The PhD work, in turn, has been carried out at the Department of ICT and Natural Sciences (IIR) at NTNU in Ålesund. The main supervisor was Professor Robin Trulssen Bye, whilst Professors Ottar Laurits Osen and Thor Inge Fossen participated in the co-supervision of this thesis from the beginning of the PhD period.

During my PhD, I have also been affiliated with the Centre for Autonomous Marine Operations and Systems (AMOS), which is a Norwegian Research Council Centre of Excellence (project number 223254). AMOS has been a great environment for networking and has been exceptionally inspiring from a research perspective.

Looking back, I have always had this unstoppable curiosity and drive to explore, discover and challenge myself for as long as I can remember. This has led me to study and work in a field that I consider quite demanding and futuristic. Pursuing a PhD in the field of autonomous ships was a natural, albeit very big, next step after completing my bachelor's and master's studies in Intelligent Robotic Systems at the Faculty of Computer Science and Information Technology at Riga Technical University (RTU), Latvia. Having finally reached this major milestone, I am of course extremely grateful for what I have learned along the path, but also puzzled and humbled by the size and complexity of the body of human knowledge today.

# Abstract

Recently, there has been an increased focus on developing an autonomous shipping technology that is safe, trustworthy, and efficient. Some enablers of this technology are strategies to advance sustainability and reducing $CO_2$ emissions. This is achieved by making ships more efficient, increasing safety and reducing the number of accidents caused by human errors on water, and reducing operational costs. However, there are still many challenges to face before autonomous technology on the water becomes a part of our daily life.

A safe and reliable path planning and collision avoidance method is an important component in autonomous shipping and plays a key role in incorporating this technology into our daily lives. Although numerous path planning algorithms for autonomous vessels have been developed, each with its own benefits and limitation, there is no one ultimate path planning and collision avoidance algorithm that is suitable for every vessel, in all water regions and in all scenarios. There is also no unified way of evaluating and comparing these algorithms to find the most suitable one for the chosen use case.

In this context, the main purpose of this research is to propose a strategy for a unified evaluation and comparison of path planning and collision avoidance algorithms. To achieve this goal, it is essential to first gain an understanding of path planning and collision avoidance as a part of the autonomous surface vehicle's guidance, navigation, and control system. There are two main application cases. First, it could be used as an offline benchmarking tool to evaluate and compare the algorithms. Second, it could be used online on an actual vessel to select the safest and most efficient path in the planning phase based on the current situation.

This thesis presents an evaluation simulator platform (ESP) for evaluating path planning and collision avoidance algorithm performance for autonomous surface vehicles. In particular, the work focuses on an extended collision risk assessment (ECRA) method for evaluating the generated paths from a safety perspective. The testing results indicate that the proposed approach could be used for autonomous path planning and collision avoidance algorithm evaluation and comparison with some improvements.

# Acknowledgment

First and foremost, I would like to express my deepest gratitude to my main supervisor Robin Trulssen Bye, Professor at the Department of ICT and Natural Sciences, for his outstanding guidance, support and sharing of knowledge that successfully walked me through these four years. I am extremely grateful to my co-supervisors Professors Ottar Laurits Osen and Thor Inge Fossen for your valuable contributions and guidance in the development of this thesis. Special thanks go to Ottar L. Osen for your valuable advice and support when I just moved to Ålesund to start my life there.

I would like to express my appreciation to the postdoctoral researchers Rachid Oucheikh and Ramesh Chandra with whom I was lucky to work and write papers. Thanks also go to my colleagues at Cyber-Physical Systems Lab and Risky Fridays group for their support, fruitful and interesting discussions, feedback and critical questions. I would like to extend my sincere gratitude to Professor Agris Niķitenko from Riga Technical University, who was my supervisor for my bachelor's and master's theses. Thank you for establishing connections with NTNU in Ålesund, being supportive of my ambitions, and planting a passion for robotics and high technology in me.

I am also grateful for my *Trap team*, Yaël and Ronny, for going on the craziest mountain adventures (they were always a trap), exploring the beautiful Sunnmøre Alps, conquering Mount Kilimanjaro, *the roof of Africa*, and sharing so many meaningful moments together. My experience in Ålesund during the PhD would not be the same without my closest friends here, Sigrid, Aleksander, Ineta and Erik. I am grateful for all the adventures, hikes, and barbecues we had together, and for being part of my Ålesund family. I also had the pleasure of meeting many wonderful (mostly) international friends in Ålesund who made this time special.

Writing this thesis would have never been possible without the support of my family. Special thanks go to my mom Vija for being the greatest inspiration and role model, showing that everything is possible with hard work, and defending her doctoral thesis at the age of 51.

Last but not least, words cannot express my gratitude to my boyfriend Torstein, who was always there for me, believed in me, and gave me all the love, encouragement, and support I needed.

# Contents

# List of Publications

This dissertation is presented as a main body and collection of publications. This thesis is based on research resulting in three peer-reviewed journal articles and two conference papers. Here and in the Appendix, the publications are presented chronologically.

**Paper A1**

**Vagale, A.**, Oucheikh, R., Bye, R.T., Osen, O.L., Fossen, T.I. *Path planning and collision avoidance for autonomous surface vehicles I: a review.* Journal of Marine Science and Technology. 26, 1292–1306 (2021). DOI: 10.1007/s00773-020-00787-6

**Paper A2**

**Vagale, A.**, Bye, R.T., Oucheikh, R., Osen, O.L., Fossen, T.I. *Path planning and collision avoidance for autonomous surface vehicles II: a comparative study of algorithms.* Journal of Marine Science and Technology. 26, 1307–1323 (2021). DOI: 10.1007/s00773-020-00790-x

**Paper A3**

**Vagale, A.**, Bye, R. T. and Osen, O. L. *Evaluation of path planning algorithms of autonomous surface vehicles based on safety and collision risk assessment.* OCEANS 2020 MTS/IEEE Global: Singapore - U.S. Gulf Coast. pp 1–8.
DOI: 10.1109/IEEECONF38699.2020.9389481

**Paper A4**

**Vagale, A.** *Evaluation simulator platform for extended collision risk of autonomous surface vehicles.* Journal of Marine Science and Engineering. 2022; 10(5):705. DOI: 10.3390/jmse10050705

**Paper A5**

**Vagale, A.**, Osen, O. L., Brandsæter, A., Tannum, M., Hovden, C. and Bye, R. T. *On the use of maritime training simulators with humans in the loop for understanding and evaluating algorithms for autonomous vessels.* The 4th International Conference on Maritime Autonomous Surface Ships (ICMASS) 2022, Singapore, pp 1-13.

### Publication not Included in this Thesis

The following paper was also produced during the duration of this research, but is not discussed in this thesis due to little overlap with the main topic of the dissertation.

**Paper A6**

**Vagale A.**, Šteina L., Vēciņš V. *Time series forecasting of mobile robot motion sensors using LSTM networks.* 2021 Applied Computer Systems 26(2):150-157.

# List of Abbreviations

| | |
|---|---|
| AIS | Automatic identification system |
| AL | Autonomy level |
| AMOS | Centre for Autonomous Marine Operations and Systems |
| APE | Algorithm performance evaluation |
| ASV | Autonomous surface vehicle |
| CCDWA | COLREG-Compliant Dynamic-Window Algorithm |
| COLAV | Collision avoidance |
| COLREG | The International Regulations for Preventing Collisions at Sea |
| CPA | Closest point of approach |
| CRA | Collision risk assessment |
| CRI | Collision risk index |
| DCPA | Distance to the closest point of approach |
| DR | Dynamic risk |
| DSM | Dynamic safety map |
| DSS | Decision support system |
| ECRA | Extended collision risk assessment |
| EMSA | European Maritime Safety Agency |
| ESP | Evaluation simulator platform |
| FIS | Fuzzy inference system |
| GNC | Guidance, navigation and control |
| GPS | Global positioning system |
| HR | Historic risk |

| | |
|---|---|
| JMSE | Journal of marine science and engineering |
| JMST | Journal of marine science and technology |
| MASS | Maritime autonomous surface ship |
| MISO | Multiple-input and single-output |
| NMCC | Norwegian Maritime Competence Center |
| NTNU | Norwegian University of Science and Technology |
| PSO | Particle swarm optimisation |
| PhD | Philosophiae Doctor |
| RTU | Riga Technical University |
| RMS | Root mean square |
| RO | Research objective |
| ROC | Remote operation centre |
| RQ | Research question |
| SCC | Shore control center |
| SDG | Sustainable development goal |
| SR | Static risk |
| SSM | Static safety map |
| TCPA | Time to the closest point of approach |
| USV | Unmanned surface vehicle |

# List of Figures

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# Structure of the Thesis

This thesis follows the format of a collection of scientific publications produced during the PhD project. The thesis consists of two parts — the main body and the appendix.

The main body lays out the research strategy, process and contributions, as well as describes how the produced publications answer the research questions. It is structured as follows. Chapter 1 provides an introduction to the research field, discusses delimitations of this study, introduces the research questions and objectives, as well as summarises contributions. Chapter 2 covers background in several topics in connection with this thesis. Chapter 3 presents the interconnection of the research questions, research objectives, and scientific papers, as well as discusses the main contributions of this thesis in detail. Finally, chapter 4 concludes the dissertation, summarises the contributions, and indicates some objectives for future work.

The appendix contains five scientific publications in the format they were submitted/published.

# 1 Introduction

Autonomous transportation is in the process of demonstrating its potential for improving multiple aspects of day-to-day life. There is a recent rapid commercial development of electric and partially autonomous cars, however, safety remains one of the key issues [6]. The shipping domain is attempting to follow this trend, as the global research interest in autonomous surface vehicles (ASVs), and more specifically their safety, is greatly increasing. The main motivation for introducing autonomy on waters is twofold.

First, the "Annual Overview of Marine Casualties and Incidents 2021" [7] from European Maritime Safety Agency (EMSA) states that:

- the navigational casualties, constituted by collision, contact, and grounding/stranding, represent 43% of all casualty events;
- 41% of the casualties occurred in internal/congested waters (more precisely in port areas); and
- from 2014 to 2020, 89.5% of all occurrences were related to human action, either at accident event or contributing factor levels.

These statistics reveal a high number of navigational casualties on water, and that a considerable part of them are caused by human action. This is where a safety-focused unmanned autonomous navigation system could improve safety on waters, reduce the number of casualties, and save human life.

Second, automation in this domain can lead to more efficient energy consumption and lowered environmental footprint. Seventeen Sustainable Development Goals (SDG)[1] are at the core of the 2030 Agenda for Sustainable Development [8]. The evolution of autonomous shipping, in general, could contribute to several of the SDGs (see Fig. 1.1 [8]), for example by bringing affordable and cleaner energy (SDG 7), and contributing to climate action (SDG 13) as a result of autonomous or reduced-emission ships that are more efficient and have fewer or no emissions. In addition, improved and more resilient infrastructure, transporting more goods on water, and improved public marine transportation

[1] https://sdgs.un.org/goals, accessed on 24 May 2022

in cities are some by-products of introducing ASVs. This, in turn, could contribute to SDG 9 (“industry, innovation and infrastructure”), and SDG 11 (“sustainable cities and communities”).


Figure 1.1: A sample of sustainable development goals that autonomous shipping could contribute to.

An important component of the SDGs and a trending topic globally is the green shift. In the shipping domain, that can be achieved through: (i) the transfer to alternative energy with fewer/zero emissions, and (ii) more energy-efficient navigation on waters. The alternative fuels with reduced emissions are still in the development phase and are not used widely enough to see a visible impact yet. On the other hand, energy efficiency could give results sooner and easier. Moreover, efficient consumption of energy on vessels is often a consequence of autonomous route planning using one of the many optimisation techniques. Autonomy in shipping and introducing unmanned vessels could also contribute to other factors; namely, opening up space for larger cargo capacity, reducing crew costs that lead to reduced operational costs, reducing operational risk attributed to human error, increasing crew safety, and increasing productivity. The autonomous and unmanned operation could also aid in promoting smaller ships as more competitive compared to larger ships due to reduced manning costs per unit.

Introducing autonomous vessels comes with its challenges, and safe and reliable testing of the new technology is one of them. With this in mind, testing an autonomous guidance, navigation and control (GNC) system in a simulator is appealing, while testing on real vessels could be costly, time-consuming, impractical and potentially dangerous. With a large amount of path planning and collision avoidance algorithms for ASVs or unmanned surface vehicles (USVs) out there, it is of high interest to find a strategy for evaluation, comparison, and testing of these algorithms. The high focus on safety and efficiency in the maritime domain indicates that these factors should be included in such an evaluation method. It should be considered that, in some cases, safety and efficiency could be at the opposite ends of the spectrum. Hence, finding an appropriate evaluation method that considers and combines various factors is often challenging.

This thesis addresses the evaluation of path planning and collision avoidance algorithms for ASVs with a focus on safety assessment and proposes an evaluation simulator platform (ESP) for a unified algorithm evaluation. The next sections define the research questions, objectives, and methodology, followed by delimitations. Contributions relating to the thesis are summarised at the end of this section.

## 1.1 Research questions and objectives

The main purpose of this study is to explore path planning and collision avoidance algorithms for ASVs, and to discover a strategy for how such algorithms (and their generated paths) could be evaluated and compared. The goal of the evaluation is to find the most appropriate algorithm (path) for each scenario. With that in mind, three research questions have been introduced. Subsequently, seeking answers to the research questions above led to formulating four research objectives.

The first research question (RQ1) aims at identifying the main components that need to be considered when developing a path planning and/or collision avoidance algorithm for autonomous ships.

> **Research Question 1 (RQ1):**
> What are the main components to consider when developing a path planning and/or collision avoidance algorithm for an ASV?

Based on the first research question, one research objective (RO1) has been formulated. RO1 aims to review the current state-of-the-art and compare existing path planning and collision avoidance algorithms for autonomous vessels based on the established set of features.

> **Research Objective 1 (RO1):**
> Review the state-of-the-art of ASVs and compare existing path planning and collision avoidance methods.

The second research question (RQ2) investigates how the autonomous navigation algorithms may be evaluated, with a particular focus on assessing collision risk.

> **Research Question 2 (RQ2):**
> How to evaluate autonomous navigation algorithms for ASVs with an emphasis on collision risk assessment?

In an attempt to answer this research question, a framework for this purpose is proposed in research objective 2.

With the input from RO2, the third research objective (RO3) aims at implementing a prototype of an evaluation simulator platform with a focus on the collision risk assessment that could be used for autonomous path planning and collision avoidance algorithm comparison.

**Research Objective 2 (RO2):**
Propose a framework for ASV path planning and collision avoidance algorithm comparison, focusing on collision risk and safety assessment.

**Research Objective 3 (RO3):**
Develop and implement an evaluation simulator prototype.

With an ESP prototype in hand, the third research question (RQ3) arises, which addresses how to incorporate experienced marine navigators' knowledge and close-to-real-life scenarios in the testing process.

**Research Question 3 (RQ3):**
How can the proposed method be utilized in real-life scenarios for algorithm validation?

As a way to answer this research question, research objective 4 (RO4) was formulated, which aspires to propose a strategy for using maritime training simulators for testing and validating these algorithms.

**Research Objective 4 (RO4):**
Discuss/propose a strategy for using maritime training simulators for algorithm testing and validation.

## 1.2 Research methodology

This research can be divided into four stages that are, in turn, split into two tracks: the main track and the side track (see Fig. 1.2). The four stages are:

1. literature review (Papers A1 and A2),
2. method development (Papers A3 and A4),
3. implementation and validation (Paper A4), and

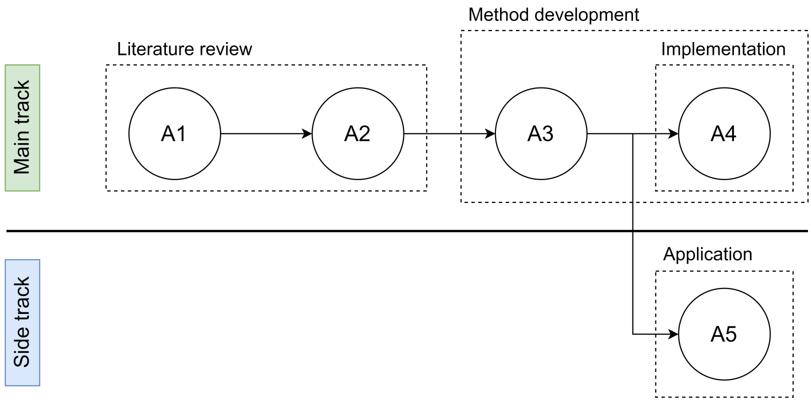


Figure 1.2: Structure of the research process and the corresponding scientific papers.

4. application case (Paper A5).

The *main track* has been the primary focus of this research and contains four Papers A1–A4 written in a consecutive manner. As a *side track*, a supplementary idea of utilising maritime training simulators for more realistic testing of algorithms with human-in-the-loop in more realistic scenarios is proposed in Paper A5.

**Literature review**

In the first stage, a state-of-the-art was reviewed and presented in Papers A1 and A2. In the comparative study in Paper A2, a set of forty-five carefully selected papers containing algorithms for path planning and collision avoidance of ASVs and USVs were compared. More on the methodology for selecting the journal and conference papers used in this study can be found in Paper A2, Section 3.

**Method development**

In this stage, a method for autonomous path planning and collision avoidance algorithm evaluation and comparison was first introduced in Paper A3, and then improved and developed in Paper A4. Details on the methodology are described in the above-mentioned papers.

**Implementation**

In the third stage, in Paper A4, the proposed method was implemented and tested on selected test scenarios to validate its potential to be used for algorithm evaluation. The dataset used in this stage contains historic automatic identification system (AIS) data.

These are secondary data that were provided by the Norwegian Coastal Administration[2]. Data pre-processing steps are described in detail in Paper A4, Section 4.

Additionally, a group of nautical experts was interviewed to obtain a qualitative opinion to form a fuzzy inference system (FIS) knowledge base. The selection criteria for the nautical experts were: (i) at least 10 years of experience working as a maritime navigation simulator instructor, and (ii) at least 4 years of experience sailing at sea in Norway.

Regarding software, two platforms used for the method implementation were: (i) Unity 3D 2019.4.21f1, and (ii) MATLAB R2021a. The simulations were executed on an Intel i7 with a hexa-core processor. For more information on the tools used in the simulation and testing, read Paper A4, Section 5.

#### Application case

Finally, an application case for using maritime training simulators in autonomous navigation algorithm testing is proposed in Paper A5 as an extension/addition to the main track.

## 1.3 Delimitations

To limit the extent of this research, the focus of this thesis is on autonomous surface vehicles and, more specifically, the path planning and collision avoidance algorithms for autonomous ships. The literature review analyses different path planning and collision avoidance algorithms for both autonomous and unmanned surface vehicles (USVs). Since the technology for the required autonomous navigation system in both cases is similar, the proposed method could also be used for decision support systems (DSS) on surface vessels.

In real ship-ship encounter situations, when avoiding collisions on water, it is important to consider safety regulations, such as International Regulations for Preventing Collisions at Sea (COLREGs) [9]. These regulations are often a part of collision avoidance algorithms or DSS that focus on safe navigation. However, in this thesis, COLREGs have not been implemented as part of the safety and risk assessment method due to the complexity of its interpretation and implementation. Based on the analysis by Zhou et al. [10], there is a need for further elaboration and amendments to eliminate the uncertainty of interpretation of COLREGs. Nevertheless, this is not excluded from future research directions.

Similarly, for generating close to real-life scenarios, weather disturbances should also be simulated and taken into consideration. However, to simplify the proposed simulator

[2] https://www.kystverket.no/en (accessed on 31 March 2022)

that is still in its initial stages, this has been also left out for future research.

The sailing area for ships is assumed to be a coastal area, congested waters, or busy waterways. In such scenarios, the navigation algorithms of the surface vessel would encounter both risks of grounding/stranding, and collision with other target vessels in the vicinity. Open waters are of less interest in this research, as the occurrence of other target vessels in open waters is much rarer, the distance between them is larger, and there are almost no static obstacles around. However, open water with icebergs could also be of interest, assuming floating icebergs as either static or dynamic obstacles.

## 1.4 Contributions at a glance

The main contributions of this thesis are towards developing a safety and risk assessment framework for path planning and collision avoidance algorithms for ASVs. Furthermore, an extensive literature review serves as a great introduction material to the domain, identifying common challenges for ASVs.

The contributions of this thesis can be summarized as follows, with the references to papers in the Appendix.

- Elucidation and clarification of terminology related to surface vessels and GNC systems, an analysis of the existing regulatory framework for ASVs, and a suggestion for classifying path planning algorithms in Paper A1.
- Analysis and comparison of selected forty-five path planning and collision avoidance algorithms for ASVs or USVs based on extracted properties/characteristics in Paper A2. The 45 algorithms are compared from three perspectives:
  - comparison of the use of eight ship- and environment-related properties,
  - analysis of implemented safety components, and applied objective function,
  - analysis of advantages and limitations of the algorithms.
- Proposing an evaluation simulator platform for evaluating path planning and collision avoidance algorithm performance for ASVs in Paper A3.
- Establishment, implementation and validation of the ESP and its risk assessment component in Paper A4.
- Proposing the use of maritime training simulators for autonomous navigation algorithm testing and research in Paper A5.

A more in-depth discussion of these contributions is provided in Chapter 3.

# 2

# Theoretical Background

A large part of the background has already been covered in two extensive literature review papers (A1 and A2). This section extends on that review by discussing taxonomy for autonomous shipping and presenting an update on the state-of-the-art in terms of path planning and collision avoidance algorithms and risk assessment frameworks.

## 2.1 Autonomous shipping taxonomy

There has been a great amount of ambiguity regarding the terminology used in autonomous shipping. Some of it has already been addressed in Paper A1. This section presents an introduction to the terminology used regarding autonomous surface vehicles.

Autonomous shipping is a relatively new field that comes with its ambiguities in the terminology used in the literature. According to Rødseth and Nordahl [11], the definition of autonomy on a ship is "*the result of applying "advanced" automation to a ship so that it implements some form of self-governance.*" Two different guidelines for defining the level of autonomy for the surface vessels are discussed in Lloyd's Register [12] and Rødseth and Nordahl [11]. These have been reviewed in Paper A1, Section 3.1. They vary from fully manual navigation of a ship (AL0) and decision support system (DSS) (Level 1) that advises the human operator, to a fully autonomous surface vehicle (ASV) (AL6 and Level 4 respectively) without a need for any human intervention.

Another concept that often goes along with autonomous shipping is "unmanned surface vehicles". In the literature, there is frequently confusion and ambiguity about the use of the terms USV and ASV. *Unmanned surface vehicles* (USVs) can be remotely controlled from the on-shore remote operation centre (ROC) also called shore control centre (SCC) or be partially/fully autonomous [1]. On the other hand, *autonomous surface vehicles* operate without direct intervention from a human operator on-board or remotely. Although in some projects, ASVs are also unmanned, they can also be manned and have a crew and passengers on board.

Maritime autonomous surface ship (MASS) is another term referred to ASVs, used more vastly in the industry and for larger surface vessels. It is defined by the International Maritime Organization [13] (IMO) as "*a ship which, to a varying degree, can* *operate independently of human interaction.*" Although the terms ASV and MASS could refer to the same technology, Rødseth and Nordahl [11] suggest a classification for autonomous maritime vehicles (see Figure 2.1).

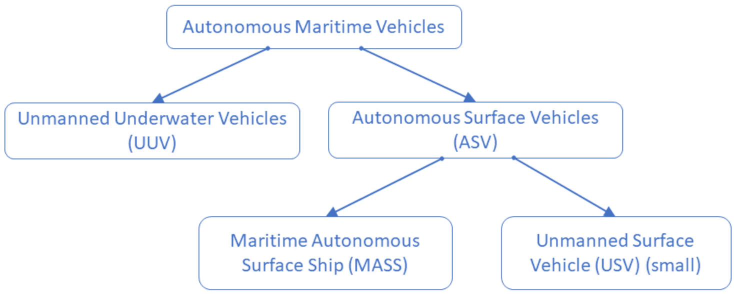


Figure 2.1: A suggestion for classification of autonomous marine vehicles types.

## 2.2 Path planning and collision avoidance algorithms

A comprehensive review of the up-to-date path planning and collision avoidance algorithms used for ASVs and USVs has been performed in Paper A2. The review paper considers algorithms developed until the year 2020. An update on the latest state-of-the-art in such algorithms is proposed in this section.

A notable review paper has been published in 2022 by Öztürk et al. [14]. The approach applied in the discussed article, comparing algorithms, is similar to the one introduced in Paper A2. The review paper analyses algorithms based on considered properties, such as water regions, COLREGs, validation techniques, and objective function type, to name a few. Another systematic review paper from 2021 by Burmeister and Constapel [15] analyses collision avoidance and path planning methods with a focus on how COLREGs have been considered/implemented in different methods.

Several individual algorithms have also been proposed and developed with several different focus aspects in 2021 and 2022. A handful of algorithms are mentioned below. In 2022, a novel improved artificial fish swarm intelligence algorithm was proposed by Zhao et al. [16]. According to the authors, the algorithm outperforms the algorithm's efficiency and path quality. The proposed algorithm has already been tested on a sea trial and proved to be suitable for practical application. With a focus on collision avoidance based on COLREGs, Kim et al. [17] have developed a COLREG-Compliant Dynamic-Window Algorithm (CCDWA) for USVs. Hybrid approaches that combine various methods for path planning and collision avoidance are also gaining a lot of attention. Krell et al. [18] have proposed a hybrid approach combining particle swarm optimisation (PSO) with visibility graphs. This reward-based planning method focuses on generating an energy-efficient path. Reinforcement learning algorithms are also being used more often in path planning and collision avoidance. One such method from 2021 by Li et al. [19] suggests combining deep reinforcement learning with artificial potential fields.

The number of newly-developed algorithms for path planning and collision avoidance in this field is significantly larger than the few methods named here. This emphasises the need for an evaluation simulator platform proposed in this thesis, as the number of new algorithms is increasing rapidly. These newly-developed algorithms just add to the large number of methods that could be evaluated and compared in the ESP.

### 2.3 Risk assessment frameworks

There have been several attempts in the scientific community to address risk evaluation for ships navigating on waters. An initial literature review on existing risk assessment frameworks is presented in Papers A3 (Section 2-B) and A4 (Section 2). This section proposes an update of some risk assessment frameworks that have not been mentioned in this research and could also be relevant.

A proactive framework for risk assessment of ship collisions in the open sea was proposed by Montewka et al. [20]. The framework uses Bayesian belief networks on simulated AIS data to analyse a wide range of risks for ship-ship collision scenarios. Another four-step risk-informed framework for risk assessment is proposed in Fan et al. [21] for the selection of an appropriate operational mode in each scenario. In this framework, risk assessment is performed on manual, remote or autonomous control operational modes to guide decision- or policymakers in selecting the appropriate operational mode. The focus there is on the identification of potential failure modes for a scenario based on an evaluation of risk priority numbers. In this case, failure modes tested were global positioning system (GPS) information loss, improper assessment of ship position, deviation in the course, improper sensing and negligence of watchkeeping.

The application and approach of different risk assessment frameworks both here and in literature reviews in Papers A3 and A4 vary greatly. However, often the risk evaluation metrics that are applied, and issues faced, remain similar. Some identified issues in the literature are automatic scenario generation for testing, producing close-to-real-life scenarios, and evaluation of good seamanship practice.

# 3 Results and Contributions

This section summarises the contributions from the articles to the corresponding research objectives. Figure 3.1 represents how research questions, research objectives and published papers are interconnected. The published peer-reviewed articles are represented in dark orange colour, while conference papers — in light orange colour. The dashed arrows indicate that findings from one RO are used in addressing other ROs. Each research objective is explained in the following sections.

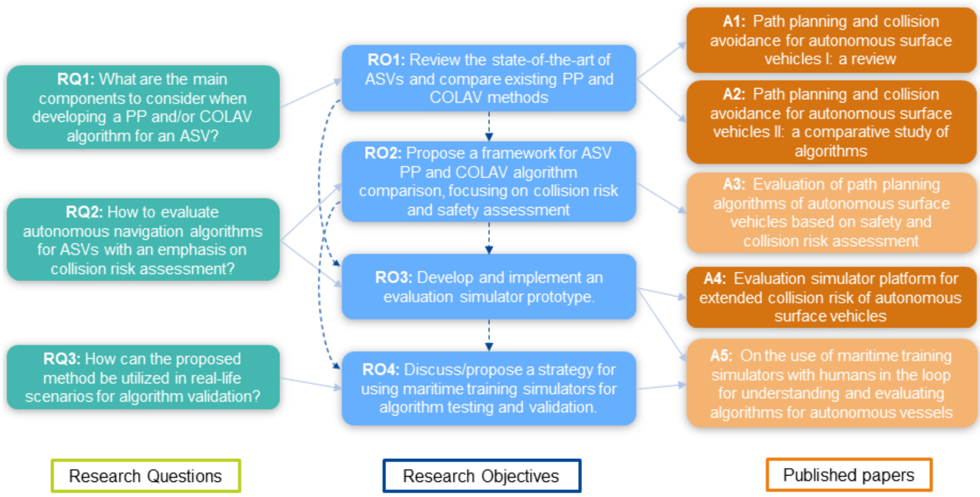


Figure 3.1: The relationship between the research questions (green), research objectives (blue) and published papers (orange). Note: PP — path planning, COLAV — collision avoidance.

## 3.1 Contribution to research objective 1

The first research objective aims at reviewing the state-of-the-art of ASVs, their navigation and guidance system, and comparing the existing path planning and collision avoidance algorithms. The contribution to this RO is twofold. First, a vast literature review is performed, in Paper A1, to get an understanding of the autonomous shipping domain and identify the components that are vital for the development of an ASV and its path planning system (Section 3.1.1). Second, forty-five carefully selected path planning and collision avoidance algorithms for ASVs or USVs are analysed and compared based on a set of defined properties and characteristics (Section 3.1.2) in Paper A2.

### 3.1.1 State-of-the-art review

Paper A1 reviews the latest advances in the autonomous vessels domain with a focus on guidance system, and path planning and collision avoidance algorithms. Some important topics covered in the review are surface vessel autonomy levels, regulatory frameworks, GNC components, advances in the industry, and up-to-date reviews in the field. The three main contributions in Paper A1 are:

- an elucidation and clarification of the terminology related to surface vessels and their guidance systems,
- an investigation of the existing regulatory framework for autonomous ships,
- a recommendation for classifying the path planning algorithms.

First, the ambiguities in the terminology around the ASV and USV, and path planning across the literature are addressed. In the maritime field, the terms ASV and USV are often used interchangeably, despite their differences. The following definitions are proposed in the paper [1].

"*An autonomous surface vehicle is a vessel that can make decisions and operate on its own, without human guidance, navigation, and control.*"

"*A USV is an unmanned vehicle that does not have a human on board to control its operations but is typically remotely controlled by a human operator.*"

The notable difference between these definitions is that an ASV operates without direct intervention from a human operator during its mission. Some identified key technologies for a vessel that is autonomous are automatic path planning and collision avoidance system, object detection capability, and autonomous decision-making system.

An attempt to clarify path/trajectory planning/generation/following/tracking terms is proposed in Fig. 3.2. Here, path planning refers to finding a path in a geometric space, whereas trajectory generation looks at a more complete picture by adding a temporal constraint to the problem.

Second, Paper A1 investigates the regulatory framework associated with autonomous vessels, such as reviewing the levels of autonomy and examining the safety regulations. As for the third contribution, a dissection of the GNC system, and a suggested classification of path planning algorithms are proposed. An interpretation of a guidance,

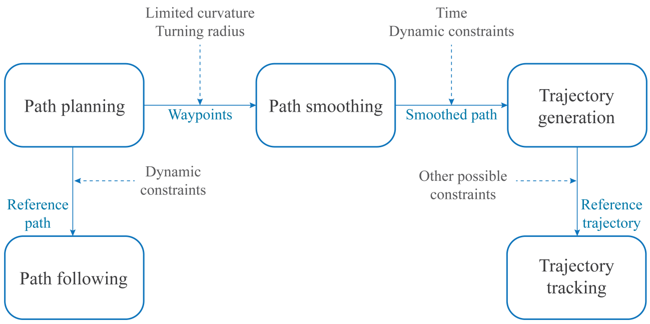


Figure 3.2: Distinction between the path planning terms used in literature. Reproduced from Vagale et al. [1].

navigation and control system architecture is proposed in Fig. 3.3 based on the literature review. The architecture proposed above is merely an attempt to propose an interpre-

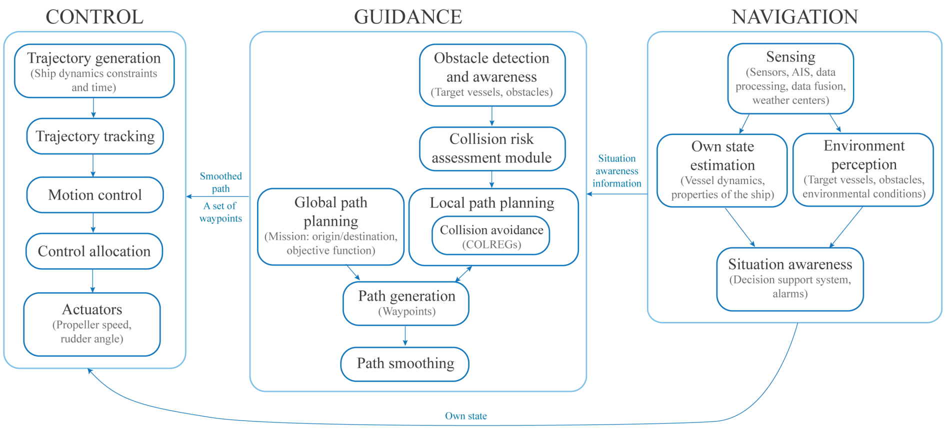


Figure 3.3: Proposed GNC system architecture. Reproduced from Vagale et al. [1].

tation of this system. Here, a path planning and collision avoidance system is included as a part of the guidance module. For a more detailed discussion on path planning algorithms and their classification, read Paper A1.

### Discussion

This work reviews and summarises some crucial components of ASVs, and serves as a guide for those entering the field without extensive pre-knowledge. The review presented here should be of interest to anyone investigating or developing intelligent path planning and collision avoidance algorithms for ASVs. Although the focus here has been on larger size vessels, many elements discussed are general across vessel sizes. Some topics for consideration are the following. The literature review has demonstrated that the confusion of terms used in this domain remains, and should be addressed in the future. A still unanswered question is whether the remote control of a ship or full autonomy should come first. A reason for concern is that, in the high-risk case of communication loss, remotely controlled vessels should have autonomy as a backup plan. Otherwise, the outcomes of an unmanned vessel without control could be disastrous.

Another topic of discussion is COLREGs rules that are initially written for human operators. In some cases, these rules are vague, which makes it complicated to measure and translate to a computer language. Also, to what extent should an autonomous vessel follow COLREGs? There might be situations when, in order to avoid a last-minute collision, the vessel should stop following the official collision avoidance rules.

### 3.1.2 Comparison of algorithms

The accompanying Paper A2 extends the work of Paper A1 to classify and compare state-of-the-art algorithms presented in forty-five peer-reviewed scientific papers. The selected papers were analysed from three perspectives.

First, eight distinguished properties were carefully extracted for the classification of the algorithms: (i) planning type (global / local / both), (ii) compliance with COLREGs (yes / no), (iii) traffic category (open waters / coastal area / congested waters), (iv) obstacle type (static / single dynamic / multiple dynamic), (v) testing type (simulation / field test), (vi) consideration of environmental disturbance (current / wind / waves / existing but unknown / no), (vii) consideration of vessel dynamics (yes / no), (viii) presence of safety domain (own safety domain / target/obstacle safety domain / no). In this analysis, a few methods for USVs are also considered. The results are presented in Figure 3.4.

Second, the article also studied the safety components and objective functions included in the analysed algorithms. Collision risk assessment (CRA) is an often-used risk evaluation measure for safe path planning. CRA may comprise several parameters, and the closest point of approach (CPA) parameter is one of them. The occurrence of time and distance to the CPA (TCPA and DCPA respectively) was analysed in the selected algorithms. The results are presented in Figure 3.5. The results demonstrate that the DCPA parameter (47%) is used more often in papers than DCPA (33%). However, less than half of the algorithms have at least one of them included.

Additionally, objective function components included in the algorithms were analysed and are summarised in Figure 3.6. The results show that the most common objective function component for the generated paths is the path length (60% of the methods), followed by path smoothness (29%), time to traverse the path (27%), and energy con-

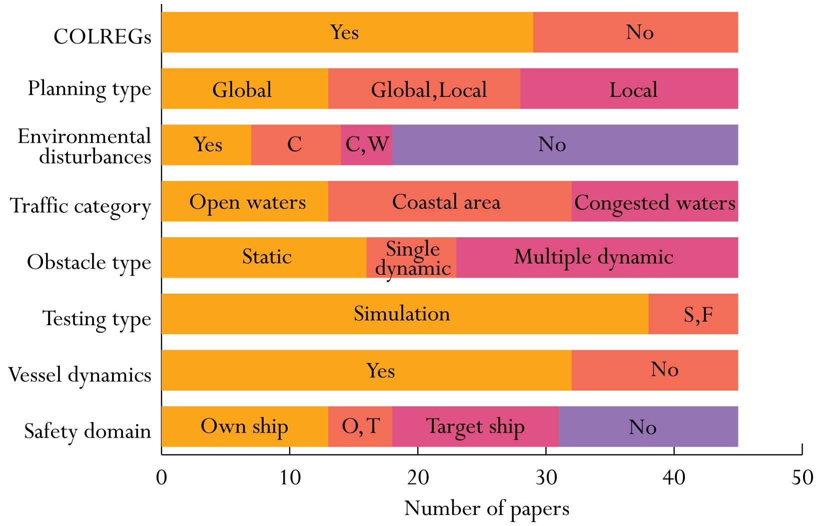


Figure 3.4: Summary of the properties among the analysed papers. Reproduced from Vagale et al. [2].

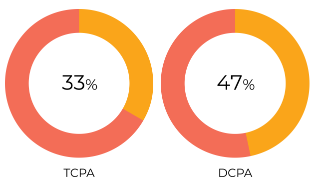


Figure 3.5: The use of TCPA and DCPA components as part of the safety assessment in the 45 analysed papers. Reproduced from Vagale et al. [2].

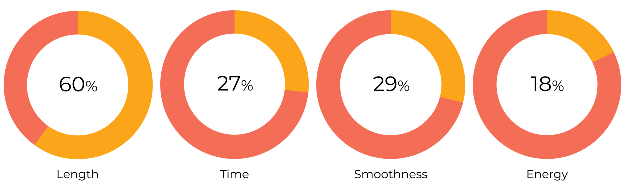


Figure 3.6: The use of objective function components in the 45 analysed papers. Reproduced from Vagale et al. [2].

sumption (18%).

Third, the advantages and limitations of the algorithms were analysed based on the information available in the papers. Some criteria for the analysis were the computational complexity, convergence, features of the planned path, ability to re-plan, real-time operation, considered complexity of environment and consideration of the local minima trap. The analysis demonstrated that, in several cases, the limitations of the algorithms are not stated clearly, while they still exist.

**Discussion**

After identifying the state-of-the-art in autonomous shipping and the vital components of an autonomous navigation algorithm for vessels, it was concluded that comparing such algorithms is a complicated task and currently there is no unified way of accomplishing that. There is still no unambiguous model of "the ultimate" autonomous ship design and components it should consider. A common tendency in the analysed algorithms is that they often perform well under specific and restricted conditions. Some common limitations in the compared algorithms are the lack of field tests or simulations with real traffic data, dealing only with static obstacles, lack of compliance with COLREGs, exclusion of weather disturbances, and other restrictive assumptions about the environment and situation. All this leads to non-realistic testing environments for vessels.

The literature review also indicates the importance of safety assessment as a part of the autonomous navigation algorithms, and that there is room for improvement. It is important to mention that the analysis of the advantages and limitations of the algorithms is subjective since it is purely based on the information provided by the authors of the algorithms.

## 3.2 Contribution to research objective 2

The second research objective is to propose a framework for evaluating path planning and collision avoidance algorithm performance for ASVs. A primary focus here is on collision risk and safety assessment. Paper A3 introduces a concept of a novel evaluation simulator platform that could be used for this purpose (see Fig. 3.7). The initial concept of an ESP suggests a technique for evaluation and comparison of path planning algorithms of ASVs in various situations. This is achieved, first, by generating scenarios under various conditions in the simulator based on the inputs. Some of the simulator's inputs are static/dynamic obstacles, environmental disturbances, different vessel dynamic models and other environmental characteristics. Second, the selected path planning algorithms are applied to each scenario to perform path planning from the start pose to the end pose. Next, each algorithm's performance is evaluated based on path fitness, safety and

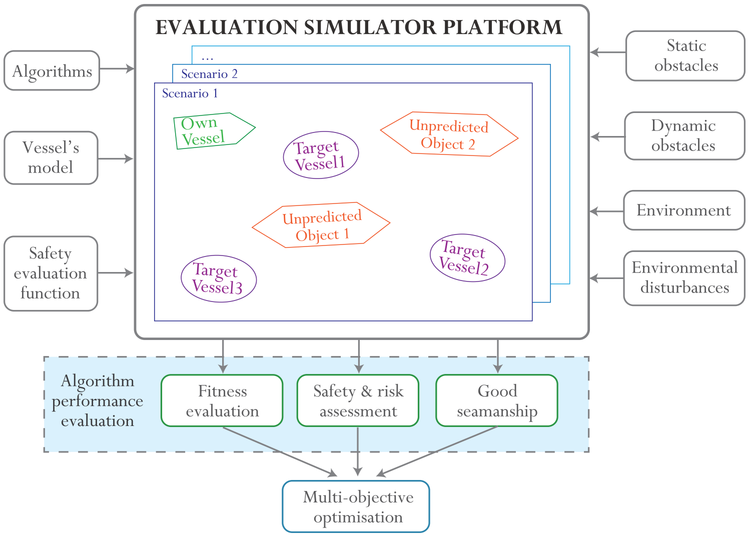


Figure 3.7: The proposed concept of the ESP for algorithm evaluation in Vagale et al. [3].

risk assessment, and good seamanship practice.

A focus area in the algorithm performance evaluation (APE) is on the safety evaluation and which includes the generation and assessment of the multi-layer safety map (see Fig. 3.8) that, in turn, may comprise several safety layers. In this case, the proposed layers are a static safety map (SSM) and a dynamic safety map (DSM). However, other types of safety layers could be included based on the requirements and needs.

This framework is significantly improved and extended in Paper A4. The improved architecture of the ESP is presented in Figure 3.9. Improvements from the initial version of the ESP are (i) a more detailed structure and (ii) an introduction of an extended collision risk assessment (ECRA) method within the algorithm performance evaluation (APE). APE is based on three evaluation factors — 1) fitness assessment of the path, 2) extended collision risk assessment method, and 3) good seamanship practice assessment. These factors are intended to be modular and easily attached or detached based on the focus and objective of the algorithm evaluation. As mentioned in Paper A3, combining these factors turns out to be a multi-objective optimisation problem. In this thesis, the second factor, the ECRA score, is implemented and has the primary focus. Fitness assessment, in this case, could include objective function parameters identified in RO1, such as path length, travel time and energy consumption while navigating.

Here, the ECRA method is significantly improved based on the safety and risk assessment module proposed in Paper A3. The results of the RO1 gave indications of

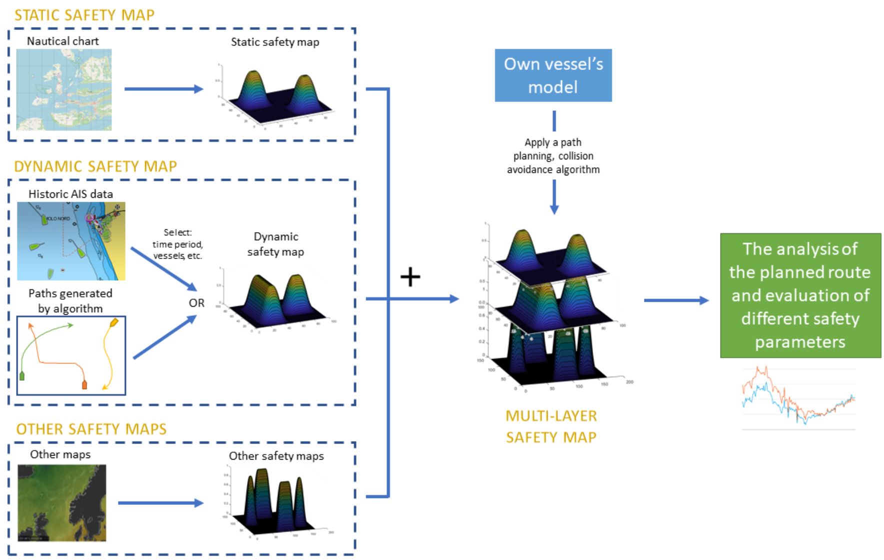


Figure 3.8: Process of the safety and risk assessment for each scenario, as in Vagale et al. [3].

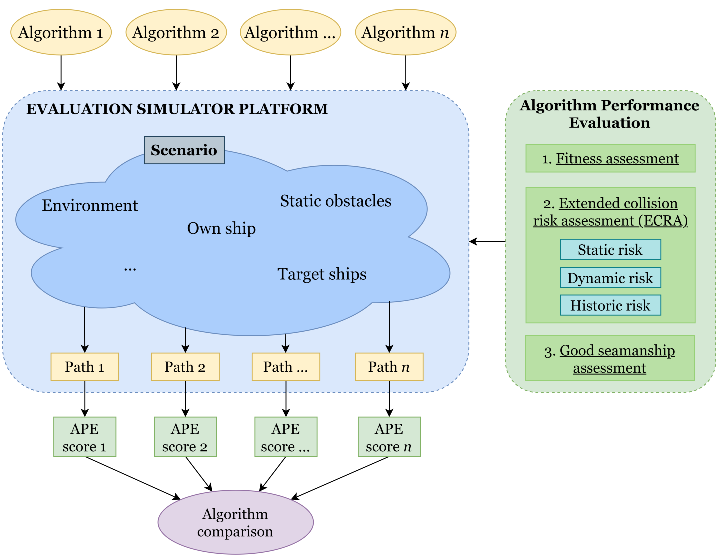


Figure 3.9: An improved ESP structure from Vagale [4].

what the researchers are focusing on when developing these algorithms, what safety aspects should be considered when navigating on the water, and common ways to assess them. Based on this, three risk factors are proposed as part of the ECRA: (i) static risk (SR), (ii) dynamic risk (DR), and (iii) historic risk (HR). The calculation of these risk factors is described in detail in Paper A4.

**Discussion**

The proposed ESP has the potential to aid in the evaluation and benchmarking of existing or newly developed path planning and collision avoidance algorithms. This simulator is intended for the simulation and evaluation of algorithms for ASVs. However, in later stages, it could be adapted also for autonomous underwater, ground or aerial vehicles.

Using AIS data in the simulator would make the scenarios more realistic. With the help of an automatic scenario generation technique, the ESP could be used for extensive testing of algorithms. At the next level, implementation of the ESP in maritime navigation training simulators would add authenticity to the scenarios.

## 3.3 Contribution to research objective 3

The third research objective aspires to develop and implement a simulator prototype for algorithm evaluation. The framework proposed in the RO2 has been established, implemented and validated in Paper A4 as a part of this research objective. The focus at this stage was on implementing the ESP, with the focus on the risk assessment component. Figure 3.10 presents a flowchart for the proposed ECRA score calculation.

At every timestep, static, dynamic and historic risk factors are calculated. Here, a static risk factor is an exponential function of the distance to the nearest static obstacles within an area of the lookout. A dynamic risk is presumed to be a collision risk index (CRI) function. An endeavour to test multiple CRI functions from the literature resulted in three selected CRI functions implemented by Kearon [22], Lisowski [23] and Mou et al. [24]. In this work, CRI is based on the TCPA ($t_{CPA}$), DCPA ($d_{CPA}$), distance to the target vessel ($d_{OT}$), spatial ($\mathcal{D}_s$) and temporal domain ($\mathcal{T}_s$) parameters. A historic risk component is based on the historic navigation patterns in the area of interest. That includes finding the possible near-miss collisions between vessels (based on the safety domain intrusion) in the historic AIS data. Afterwards, the three risk factors are combined into the individual risk value ($\mathcal{R}$) using a fuzzy inference system for each timestep (point) on the vessel's path ($\rho$). Finally, an extended collision risk assessment (ECRA) score for a path is obtained by applying a root-mean-square (RMS) function to all the individual risk values on the path. This process and methods are described

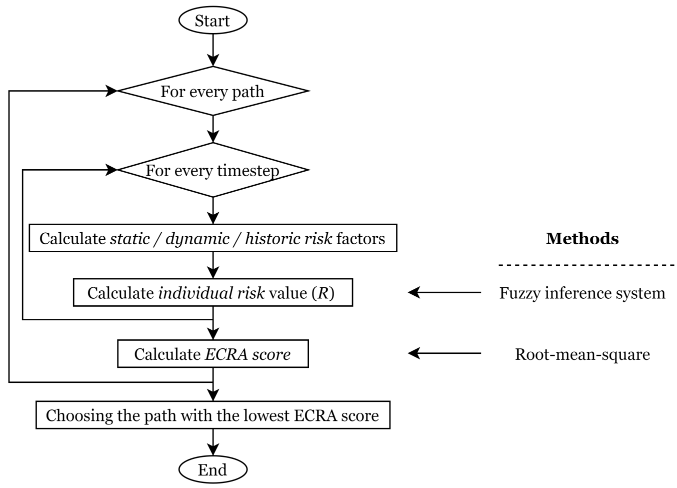


Figure 3.10: A flowchart of the ECRA score calculation, as in Vagale [4].

in more detail in Paper A4. Figure 3.11 reveals how the aforementioned methods have been implemented in software.

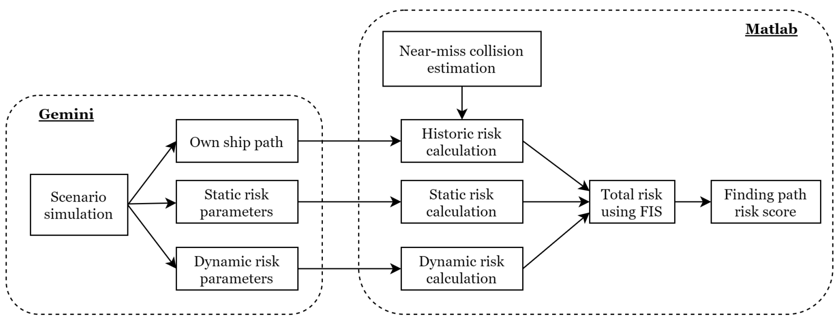


Figure 3.11: Architecture of the simulation framework used for ECRA calculation. Reproduced from Vagale [4].

The FIS used to find the ECRA score was based on experts' knowledge. Therefore, an interview with a group of nautical experts was conducted to incorporate their knowledge and experience into this research. The designed multiple-input and single-output (MISO) FIS was a type-1 Mamdani system with three inputs (SR, DR, and HR), individual risk value as output and twenty-seven rules in the expert rule base. All input variables had three linguistic states in their membership function — *low* (L), *medium* (M), and *high*(H), while the output variable has an additional linguistic state — *very high* (VH). The expert rule base obtained in this research is presented in Table 3.1.

Table 3.1: The resulting expert rule base of the total risk value based on nautical experts' knowledge. Reproduced from Vagale [4].

| | | $r_{static}$ ($r_{historic} = L$ ) | | | $r_{static}$ ($r_{historic} = M$ ) | | | $r_{static}$ ($r_{historic} = L$ ) | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | **L** | **M** | **H** | **L** | **M** | **H** | **L** | **M** | **H** |
| $r_{dynamic}$ | L | L | L | M | L | M | M | L | M | M |
| | M | M | M | H | M | M | H | M | M | H |
| | H | M | M | VH | M | H | VH | M | VH | VH |

This method has been validated using the Autoferry Gemini simulator. Three existing scenarios were selected in the simulator as the validation test setups:

1. a head-on encounter scenario with two moving vessels,
2. an entry in the channel and meeting a passing vessel from the starboard side,
3. a head-on encounter scenario with one moving and one standing vessel.

Additionally, in each test scenario, three derived paths were generated with varying degrees of safety. Altogether, results from four paths in each scenario were compared, where A is the original path, B is the cautious path, C is the incautious path regarding static obstacles, and D is the incautious path with respect to dynamic obstacles. The validation results are presented in Table 3.2.

Table 3.2: ECRA scores in three test cases for four proposed paths using three different CRI methods [4].

| | *ECRA score* | | | | | |
|---|---|---|---|---|---|---|
| Path | $CRI_1$ | $CRI_2$ | $CRI_3$ | $\mu$ | $\sigma$ | $\sigma(\%)$ |
| 1-A | 0.3305 | 0.3308 | 0.2329 | 0.2981 | 0 | 0 |
| 1-B | 0.3234 | 0.3238 | 0.2154 | 0.2875 | -0.0105 | -3.53 |
| 1-C | 0.5262 | 0.5266 | 0.3599 | 0.4709 | 0.1728 | 57.98 |
| 1-D | 0.3435 | 0.3432 | 0.2412 | 0.3093 | 0.0112 | 3.77 |
| 2-A | 0.4138 | 0.4062 | 0.4025 | 0.4075 | 0 | 0 |
| 2-B | 0.3864 | 0.3531 | 0.3800 | 0.3732 | -0.0343 | -8.43 |
| 2-C | 0.4969 | 0.4244 | 0.4431 | 0.4548 | 0.0473 | 11.61 |
| 2-D | 0.4186 | 0.3402 | 0.3772 | 0.3787 | -0.0288 | -7.08 |
| 3-A | 0.3298 | 0.3274 | 0.2213 | 0.2928 | 0 | 0 |
| 3-B | 0.3419 | 0.3417 | 0.2143 | 0.2993 | 0.0065 | 2.21 |
| 3-C | 0.3855 | 0.3853 | 0.2973 | 0.3560 | 0.0632 | 21.58 |
| 3-D | 0.3297 | 0.3294 | 0.2117 | 0.2903 | -0.0026 | -0.88 |

The results demonstrate that the ECRA score reduction for cautious paths varies up to 8.43%, while the risk for incautious paths increases up to 57.98%. Superior results are demonstrated when comparing the incautious path with respect to static obstacles. Here, the ECRA score had an increase in all three test setups. This indicates that the proposed method responds well to an attempt to improve the safety of the planned path with regard to avoiding grounding/stranding. The results for paths where dynamic risk is compromised are not completely consistent. Observing simulations indicates that, in some situations, that are more dangerous in terms of dynamic risk, the static risk factor has been significantly improved. This, in turn, has led to a lowered ECRA score in some scenarios for path D. A comparison of three CRI methods implemented in the ESP demonstrates that $CRI_1$ and $CRI_2$ respond similarly to different scenarios. Historic risk has proved to have little impact on the ECRA score. The results suggest that the proposed ESP could be used for the algorithm evaluation and comparison with some improvements.

**Discussion**

It was observed that the static risk component has a great impact on the ECRA score. In some cases, it has led to a result where a theoretically incautious path demonstrates a decrease in the ECRA score, and the opposite. It is important to note that the expert rule base obtained in this research has a high effect on the results of the simulation and the ECRA scores.

Also, some interesting findings were revealed when consulting with the group of experts. Based on their opinion, static risk has the highest importance, whereas historic risk has the least. Weather and environmental conditions should have a large impact on the ECRA score, hence this should be considered for future work when extending the ESP.

As for the limitations of the study, only two-vessel encounter situations were considered. This limitation could be addressed in future research. Tuning the fuzzy system parameters using one of the optimisation techniques is another interesting future study. The consultation with a group of experts gave several valuable inputs for the development of the ESP. With this in mind, their opinion could be used later to obtain feedback about the risk assessment decision in various scenarios, and the authenticity of the generated scenarios.

## 3.4 Contribution to research objective 4

The fourth research objective aims to discuss and propose a strategy for testing and validating autonomous navigation algorithms in a more realistic environment. Since testing autonomy on vessels in real life is potentially costly, dangerous, and risky, using maritime training simulators for this purpose provides an adequate alternative. Paper A5 suggests another strategy for how the performance and capacities of algorithms could be evaluated and tested extensively. Using maritime navigation training simulators for algorithm validation could enable standardized, reproducible, relevant, and realistic testing. Two main test setups proposed in the article are (see Fig. 3.12):

- *Test setup A* — where the bridge(s) is/are controlled by the human cadet(s) while the autonomous algorithm(s) control the target vessel(s).

- *Test setup B* — where the autonomous algorithm(s) control the bridge.

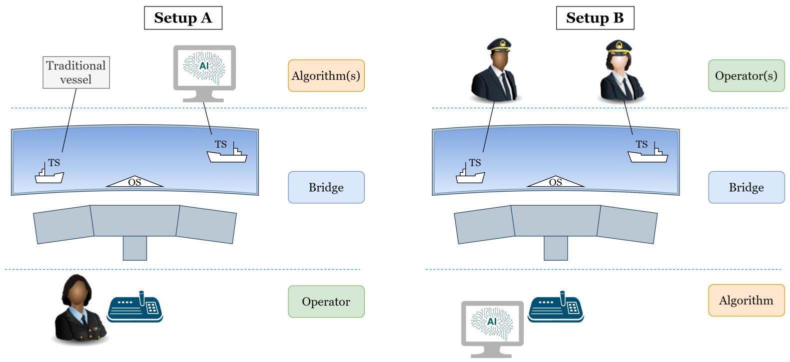


Figure 3.12: Two main test setups in maritime navigation training simulators. Reproduced from Vagale et al. [5].

Test setup A (Fig. 3.12, left) opens possibilities to study both how humans react to autonomous vessels, and how the autonomous vessels respond to human actions. This could be combined with cadet interviews after the exercise to evaluate their experience. This setup could also be used to test algorithms, similarly to Turing's imitation game.

Test setup B (Fig. 3.12, right), in turn, allows testing algorithms with respect to collision avoidance in different scenarios. The benefit of using certified maritime training simulators is their higher reliability when compared with more "Lo-Fi" simulators. An especially interesting experiment would be giving the same task to both an algorithm and a human cadet. Then, an experienced instructor could evaluate how well an algorithm performs compared to a human. The two suggested test setups are just examples, and more complex hybrid setups could be constructed by introducing other elements, combining scenarios, etc. Several other appealing research questions that arise from these test setups are discussed in Paper A5.

**Discussion**

In studies with humans in the loop, test scenarios should be authentic and realistic. Maritime navigation training simulators are deemed to be a good and realistic training environment for cadets. That makes these simulators suitable as a research environment for autonomous surface vehicles. One limitation of this idea is that it might not be easy to generalise all findings on cadets to experienced sailors. As a solution, a control group comprising experienced sailors could be subject to the same tests as cadets. All in all, these test setups have the potential to provide valuable answers to some research questions that are complicated to answer otherwise.

# 4 Conclusions

This thesis and the accompanying articles present an attempt at finding a unified approach to evaluate and compare path planning and collision avoidance algorithms, with a focus on safety. The research objectives of this PhD thesis have been successfully accomplished. The state-of-the-art in the field has been reviewed and discussed from several aspects. Together with a comparative study of algorithms, they answer the RQ1. Next, an evaluation simulator platform has been proposed, implemented and validated to answer the RQ2. Finally, a concept of using maritime training simulators for testing algorithms in close to real-life scenarios has been proposed to answer the RQ3.

These findings open up possibilities to use the proposed platform and method for validating, benchmarking or improving existing and newly developed algorithms. Furthermore, using maritime training simulators introduces closer to real-life scenarios for testing, and a great environment for answering more research questions. These findings could potentially impact the further development of safe guidance, navigation, and control system for autonomous surface vehicles. Extensive testing of these algorithms in a close to the real-life simulator, before applying them on a real ship, could lead to safer and more reliable navigation on the water.

## 4.1 Summary of contributions

This thesis contains three journal articles and two conference papers that have been published during this research, and that directly respond to the set research objectives. The contributions of this thesis can be summarised as follows.

1. Reviewing the state-of-the-art in the field from multiple aspects, elucidating the terminology used, analysing the regulatory framework, and suggesting a classification for path planning algorithms.

2. Analysing and comparing forty-five path planning and collision avoidance algorithms based on a set of extracted properties, considered safety assessment, a choice of the objective function, and advantages/limitations for each algorithm.

3. Proposing an evaluation simulator platform for assessing and comparing path plan-

ning and collision avoidance algorithm performance.

4. Implementing and validating the proposed simulation platform and risk assessment method.

5. Proposing a concept of using maritime training simulators for testing algorithms in close-to-real-life scenarios.

### 4.2 Application of the ESP

The proposed method could be used as an offline tool to test and compare existing path planning and collision avoidance algorithms in different scenarios. In such a case, the ESP could aid in finding limitations/flaws in the planning algorithms and indicate how they could be improved before they are installed on a real vessel.

On the other hand, the ESP could be used in real-time on a vessel when planning the next route. In this case, several path planning algorithms could be evaluated in the current scenario in the ESP. Next, APE scores would be calculated for each algorithm. Finally, a path with improved safety and efficiency would be indicated. A requirement for this application is having fast enough computational time to run simulations in real-time.

### 4.3 Directions for future work

The results of this research open numerous future research directions. These are mostly connected with supplementing, extending and improving the existing research.

First, conducting extensive testing of path planning and collision avoidance algorithms in the ESP would aid in validating the proposed simulator and method, and indicate potential improvements.

The next improvement could be supplementing the ESP and the ECRA score with additional risk factors, such as compliance with COLREGs, and risk connected with weather disturbances. As the ECRA score is quite modular, this process would not be too complicated.

Another interesting future direction would be a practical implementation of the idea to use maritime navigation training simulators for algorithm testing, as presented in Paper A5. NTNU in Ålesund has a close relation with Kongsberg Maritime[3] located in the Norwegian Maritime Competence Center[4] (NMCC) and their maritime training simulators. Using these training simulators would enable the evaluation and testing of autonomous path planning and collision avoidance algorithms in a more realistic

[3] https://www.kongsberg.com/maritime/, accessed on 30 June 2022
[4] https://www.nmcc.com/en/, accessed on 30 June 2022

environment and aid in answering several important research questions about human and autonomous ship interaction.

Automatic scenario generation for testing purposes is a future direction that has already been identified in Paper A3, as well as evaluation of good seamanship practice.

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# Appendix

# A

# Paper A1

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REVIEW ARTICLE

# Path planning and collision avoidance for autonomous surface vehicles I: a review

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**Abstract**

Autonomous surface vehicles are gaining increasing attention worldwide due to the potential benefits of improving safety and efficiency. This has raised the interest in developing methods for path planning that can reduce the risk of collisions, groundings, and stranding accidents at sea, as well as costs and time expenditure. In this paper, we review guidance, and more specifically, path planning algorithms of autonomous surface vehicles and their classification. In particular, we highlight vessel autonomy, regulatory framework, guidance, navigation and control components, advances in the industry, and previous reviews in the field. In addition, we analyse the terminology used in the literature and attempt to clarify ambiguities in commonly used terms related to path planning. Finally, we summarise and discuss our findings and highlight the potential need for new regulations for autonomous surface vehicles.

**Keywords** Autonomous surface vehicle (ASV) · Artificial intelligence · Path planning · Collision avoidance · Safety

## 1 Introduction

Research into path planning and collision avoidance (COLAV) algorithms for autonomous surface vehicles (ASVs) is motivated by continuing efforts to optimise operations and improve operational safety and performance. The general premise is that introducing higher levels of autonomy can reduce accidents, fuel costs, and operational costs (including crew), and improve regularity by reducing the frequency and consequence of human errors. To illustrate, the Annual Overview of Marine Casualties and Incidents 2019 [1] developed by the European Maritime Safety Agency (EMSA) states that in 2011–2018, more than 54% of all casualties with ships were navigational casualties—a combination of contact (15.3%), collision (26.2%) and grounding/stranding (12.9%) accidents. Moreover, from a total of 4104 accident events analysed during the investigations, 65.8% were attributed to human erroneous actions. Statistics also show that 41.7% of all casualties took place in port areas, followed by 27.4% in the coastal areas (territorial sea). These numbers indicate an increased collision risk when navigating in congested waters with several static and dynamic obstacles. The aforementioned high percentage of navigational casualties (54.4%) and attribution to human erroneous actions (65.8%) for human-controlled ships can likely be reduced by introducing autonomy in the operation of surface vessels. In addition, autonomous vessels are well suited for missions in dangerous and rough sea environments, for example by better real-time decision-making or in the case of unmanned vessels, removing the risk of human lives. On the other side, increased autonomy is also associated with several important challenges related to operation in open, coastal, and congested waters, energy consumption, environmental abnormalities, personnel requirements, and national security issues that need to be considered.

The autonomous ship market is expected to grow at a fast rate in the near future. According to Global Autonomous Ship and Ocean Surface Robot Market: Analysis and Forecast, 2018–2028, a market intelligence report by BIS Research [2], "the autonomous ship market in terms of volume is expected to grow at the rate of 26.7% during the period 2024–2035 and cumulatively generate a revenue

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of $3.48 billion by 2035." Hence, we expect to see an increased demand for the development of autonomous systems technology in the maritime industry, and for ships in particular.

To enable safer systems on waters with increased autonomy requires development of improved and reliable guidance, navigation and control (GNC) systems. The focus of this paper is on guidance systems, and more precisely on path planning and collision avoidance algorithms. Looking at the research done in the field so far, it is of our interest to address the ambiguities in the terminology, investigate the regulatory framework associated with autonomous vessels, and decompose the GNC system of an ASV to review different types of path planning algorithms. Our research aims at summarising the main components that need to be considered when developing a path planning and/or collision avoidance algorithm, based on information available up to date. Whereas much of what we present is general across vessel size, other considerations will differ whether the vessel is a small boat or a large ship. In such cases, the reader should note that larger ships are our main focus.

The three main contributions of this paper can be summarised as follows: (i) an elucidation and clarification of terminology related to surface vessels and guidance systems; (ii) an analysis of the existing regulatory framework for ASVs; and (iii) a suggestion for classifying path planning algorithms. Thus, our work should be of interest for investigators and developers of intelligent algorithms for path planning and collision avoidance for ASVs. Indeed, in an accompanying article in this journal [3], we extend the classification scheme presented here, and analyse and classify algorithms presented in 45 different peer-reviewed scientific papers.

The remainder of this paper is organised as follows: Sect. 2 presents advantages, challenges, and current development of ASVs, defines terminology used within this scope, and provides an overview of previous survey papers. Section 3 details regulatory guidelines that define autonomy and control safety of ASVs. Section 4 presents the authors' view on the GNC modules for ASV navigation, from the perspective of path planning and collision avoidance. Section 5 provides our proposed classification of path planning algorithms. Section 6 contains a discussion, and finally, some concluding remarks are drawn in Sect. 7.

## 2 Background

This section presents advantages and challenges of ASVs and recent advances in the industry, clarifies some of the terminology used in the literature, and provides an overview of previously published review papers in the field.

### 2.1 Advantages and challenges of ASVs

ASVs have the potential to outperform traditional vessels with regard to safety. An increased adoption of ASVs could lead to a reduction in accidents caused by human erroneous actions, which currently contribute to a large share of ship casualties. However, the advantages of ASVs are not limited only to the safety aspect. Below, we identify some current, and potential future, advantages of ASVs:

- Reduced, or eliminated, need for human control and hence, human errors.
- Longer duration performance and enabling more hazardous missions than manned vehicles.
- Improved reliability compared to remotely controlled unmanned surface vehicles (USVs) that demand highly reliable and secure communication means, and for which failure of communication may lead to a loss of navigation, accidents, or disaster.
- Enhanced controllability and deployability, in addition to increased flexibility in sophisticated environments, including so-called dirty, dull, harsh, and dangerous missions.
- Reduced personnel costs and improved personnel safety and security, when no crew is onboard and collision avoidance intelligence is implemented.
- Extended operational capabilities, functionality, and precision, which also make ASVs increasingly required in many fields, e.g., scientific research, environmental and hydrographic surveys, ocean resource exploration, military operations, and other applications.
- Reduced risks of piracy, including elimination or kidnapping of crew members.
- Increased available space and tonnage for cargo by eliminating the need for life support systems and crew facilities (hotel, catering, and sanitary rooms).
- Reduced design constraints from not having humans operating the vessel.
- Removed need for a traditional navigation bridge by placing sensors optimally anywhere on the vessel.

Importantly, autonomy is the means to ensure these advantages and not a goal in itself. Moreover, ASVs are still facing several challenges before global commercialisation and operations in international waters. Some of these issues are identified below:

- *Regulatory framework.* Legislation regulating ASVs is still unclear. Significant international cooperation is required in order to set up navigation and safety regulations as well as the design standards.

- *Liability.* There are many legal challenges that arise if there is no captain onboard, e.g., who is liable for the actions being made.
- *Cyber-security.* A big concern for all autonomous systems, cyber-security is of vital importance. A flaw in software may give unauthorised access to hackers who could take control of a ship.
- *Safety in navigation.* A vessel sailing in open waters faces many risks including harsh weather conditions, obstacles, especially dynamical or underwater, or even risks related to third parties. Special attention should be brought to obstacles that cannot be detected by the automatic identification system (AIS), such as people in water, recreational vessels, small water equipment, or sea animals. An autonomous ship must be able to handle such challenges by itself without human control.
- *Reliability and maintenance.* To operate at deep-sea for extended periods of time it is crucial to have good condition monitoring systems, maintenance plans, and redundancy. If there are no engineers onboard, the planned maintenance must take place at port. This may require longer stays in port, and vessel off-hire is expensive. Furthermore, to achieve satisfactory reliability, it may be required to redesign many of the ship systems to improve the mean time between failure (MTBF) and add redundancy.
- *Connectivity.* Even though there is an increasing number of satellites in orbit, there is a varying degree of coverage and bandwidth depending on vessels' location. Areas at high latitudes have poor coverage and are particularly challenging since most satellites are geostationary above the equator. In addition, a vessel could lose connectivity due to weather, damage to crucial equipment (such as antennas), and interference.
- *Piracy.* Even if the ASV is unmanned, the cargo and the ship itself have a high value and is subject to hijacking. An unmanned ship may also be easier to seize.

## 2.2 Recent advances in the industry

Nowadays, leading shipbuilding companies already have a vision of a future with mostly autonomous vessels on waters. In what follows, we present some recent advances and future predictions among important actors in the industry.

In their €6.6 million project, Advanced Autonomous Waterborne Applications Initiative (AAWA) (2015–2017), Rolls-Royce anticipated having ocean-going autonomous ships by 2025 [4]. Moreover, in 2017, Rolls-Royce, in cooperation with Svitzer, demonstrated project Sisu—the world's first remotely operated commercial vessel [5]. Subsequently, in 2018, Rolls-Royce in cooperation with Finferries started the collaboration project Safer Vessel with Autonomous Navigation (SVAN) to test the findings of the AAWA project

**Fig. 1** "The world's first fully autonomous ferry" Falco by Finferries


**Fig. 2** USV Otter by Maritime Robotics

[6]. The aim of the project is to develop solutions to optimise the safety and efficiency of ships. So far, they have succeeded in designing and commercialising components for automatic operations such as autocrossing systems, which resulted in "the world's first fully autonomous ferry" Falco[1] (see Fig. 1) successfully demonstrated in 2018 [7]. Furthermore, in another joined collaboration with Intel, Rolls-Royce is trying to make autonomous ships a reality by providing new technologies, intelligent awareness systems, and other products to enhance the operational safety of ASVs [8]. Finally, it is worth mentioning that the Rolls-Royce division mainly involved with autonomous ships, Rolls-Royce Commercial Marine, recently was acquired by Kongsberg Gruppen [9].

A Norwegian company, Maritime Robotics, has developed the USV Mariner [10], a multipurpose unmanned vehicle for offshore and coastal applications, and the USV Otter[2]

[1] https://gcaptain.com/another-fully-autonomous-ferry-demonstrated-in-northern-europe/.

[2] https://sonar-nusantara.co.id/otter-usv/.

**Fig. 3** USV Rakuten K22 as a result of cooperation between Maritime Robotics and Rakuten Institute of Technology


**Fig. 4** Yara Birkeland as a result of cooperation between Yara and Kongsberg Maritime

(see Fig. 2) [11], an easily deployable system for seabed mapping and monitoring of sheltered waters. In addition, Maritime Robotics in cooperation with Rakuten Institute of Technology has developed a zero-emission USV Rakuten K22[3] (see Fig. 3) for research of unmanned cargo ships and related technologies as a logistics solution [12].

The Norwegian companies Yara and Kongsberg Maritime have succeeded in designing an all-electric, autonomous container ship known as Yara Birkeland[4] (see Fig. 4), which is expected to operate fully autonomously by 2022 [13]. Subsequently, the prominent shipping industry companies Wilhelmsen and Kongsberg Maritime decided to create the Massterly autonomous shipping company that will provide vessels' autonomous operations, design and development, and control systems [14].

At the time of preparation of this review, the classification company DNV GL is working on a project developing an

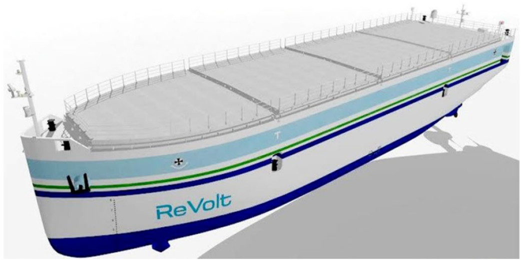


**Fig. 5** The ReVolt by DNV GL

unmanned, zero-emission, shortsea vessel, the ReVolt[5] (see Fig. 5) [15], as a solution to the growing need for transport capacity.

The Japanese companies Mitsui O.S.K. Lines and Mitsui Engineering & Shipbuilding Co. joined in a project of developing technology for autonomous ocean transport systems and are planning to have autonomous ships by 2025 [16]. The Japanese NYK and NYK Group companies MTI Co. Ltd, Keihin Dock Co. Ltd and Japan Marine Service Inc. are also working on developing an autonomous ship, focusing on the collision risk judgement and the autonomous operation of vessels [17]. This Japan's first demonstration project for autonomous ships was presented in August 2018.

Meanwhile in Finland, according to Maritime Journal [18], company ABB has made a step forward with their research on autonomous shipping by successfully demonstrating remotely operated passenger ferry Suomenlinna II. Another Finnish project, Dimecc's innovation ecosystem project One Sea (2017–2025) for autonomous marine transport uniting almost 80 companies, is planning to create the "world's first autonomous marine transport system to the Baltic Sea" [19]. The ecosystem anticipates having fully autonomous ships by 2025.

Several big governmental projects draw some broad lines for accelerating the development of ASVs. The USV Master Plan [20] established for the US Navy lists objectives for improving autonomy to increase mission diversity and reduce the amount of supervisory intervention. Additionally, the Department of Defense of the US military published another report entitled Unmanned Systems Integrated Roadmap [21] that articulates a vision and strategy for the continued development, production, test, training, operation, and sustainment of unmanned systems. Resurging interest in ASVs came especially with the Defence Advanced Research Projects Agency's (DARPA's) announcement that it required

[3] https://global.rakuten.com/corp/news/press/2018/0313_02.html.

[4] http://www.marinteknikk.no/headlines/2018/mt2007-yara-birkeland-3.

[5] https://www.bluebird-electric.net/artificial_intelligence_autonomous_robotics/Revolt_DNV_GL_ASV_Unmanned_Battery_Cargo_Vessel.htm.

$3 billion in fiscal 2012 for projects involving ASV development for submarine tracking.

Furthermore, a collaborative research project, co-funded by the European Commissions under its Seventh Framework Programme named Maritime Unmanned Navigation through Intelligence in Networks (MUNIN) (2012–2015), was working to develop technology for unmanned and autonomous vessels [22, 23]. The total budget of the project was 3.8 million EUR. Besides showing the technical, economic and legal feasibility of ASVs and USVs, it aimed to develop IT architecture for autonomous operation and design the individual components of the ASVs.

To summarise, it is clear that several companies worldwide are currently actively working towards the development of ASVs and USVs due to their benefits and novelty. The predictions of most of these companies state that fully autonomous ships can be expected by 2025.

## 2.3 Terminology

A review of the literature shows that there has been a great deal of ambiguity regarding the terms used in the field. Noticing this diversity, we aim at distinguishing the terminology used regarding the types and features of surface vessels, as well as the differences between terms used in path planning and path following, based mostly on LaValle [24], Lekkas [25], Fossen [26]. The definitions below are our attempt at harmonising and complementing the terms used.

### 2.3.1 Autonomous versus unmanned surface vehicles

The use of terms like ASV and USV across the literature is not always uniform and in some cases is even confusing. For example, a *surface vessel* may be defined as a "nonlinear underactuated kinodynamic system often with large inertia" [27] that operates in continuous contact with the surface of the water. However, many modern vessels are fully actuated and their inertia need not necessarily be large.

An *autonomous surface vehicle*, or ASV, on the other hand, is a vessel that can make decisions and operate on its own, without human guidance, navigation, and control. ASVs are typically used in military operations, maritime surveillance cruises, marine environmental monitoring applications, and in the near future, likely also for the transportation of goods and people.

Many papers in the field are referring to the terms ASV and *unmanned surface vehicles* as synonyms, and do not distinguish the methodology for these two types of vessels. A USV is an unmanned vehicle that does not have a human on board to control its operations but is typically remotely controlled by a human operator. Crucially, an ASV *may* also be unmanned but the important distinction, when compared with a USV, is that it operates without direct intervention from a human operator during the course of its 'mission,' whatever that might be. Obviously, an ASV could have crew and passengers in the same way as autonomous cars have passengers. Nevertheless, in the maritime field, the term ASV is commonly used when talking about an unmanned vessel. Finally, to be categorised as an autonomous (or semi-autonomous vessel), some key on-board technologies are required, which include: automatic route generation and path planning techniques, object detection capability, collision avoidance capability, and autonomous decision-making systems.

### 2.3.2 Path planning terminology

Path planning is a critical part in the development of USVs in general, and for ASVs in particular, with the aim of using algorithms to determine optimal trajectories to guide a vessel's voyage. It can be defined as the problem of finding a route between two positions in a mobile space, considering that the route should be collision-free, physically feasible within spatial constraints, and satisfy certain optimisation criteria. Commonly used optimisation criteria for path and trajectory include minimisation of path length, time, and energy consumption, as well as measures of safety or risk. Also, path planning is typically defined within purely geometric space, whereas trajectory planning, or trajectory generation, involves geometric paths endowed with temporal properties, e.g., to incorporate dynamics. Although path planning of ASVs has been a focus of many authors, inconsistency of the corresponding terminology still occurs. Below, we attempt to elucidate some common terms related to path planning, with a visual representation of the terms shown in Fig. 6:

- *Path planning* aims to generate a geometric path by finding the set of waypoints to navigate through (or near) to travel from a start position to an end position.
- *Trajectory generation* succeeds the process of path planning and has a wider scope since it can take into account turning angle limits and velocity and acceleration constraints in order to generate a feasible trajectory that the ship can follow. In particular, trajectory generation includes assigning a temporal constraint (time law) to the geometric path.
- *Path following* means following a predefined path in the space which does not involve time as a constraint, and where the essential goal is to stay on the geometric path and follow it with whatever speed until the goal is reached.
- *Trajectory tracking*, on the other hand, has a time profile, meaning that the ship has to be at a certain point at a certain time while following the trajectory.

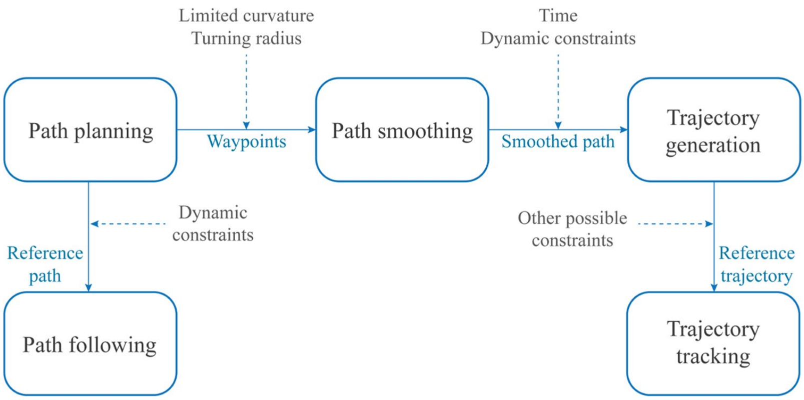


**Fig. 6** Visual representation of the distinction of path planning terms used in literature

**Table 1** List of previously published review papers

| References | Title | Keywords |
|---|---|---|
| [28] | Autonomous ship collision avoidance navigation concepts, technologies and techniques | Autonomous ship, collision avoidance, navigation factors, COLREGs |
| [29] | Review of collision avoidance and path planning methods for ships in close range encounters | Path planning, ship navigation, collision avoidance |
| [30] | A review on improving the autonomy of unmanned surface vehicles through intelligent collision avoidance manoeuvres | USVs, COLREGs, autonomy, collision avoidance, guidance, motion planning |
| [31] | A survey on path planning for persistent autonomy of autonomous underwater vehicles | Autonomous underwater vehicle, path planning, persistent autonomy, path optimization |
| [32] | Unmanned surface vehicles: An overview of developments and challenges | Unmanned surface vehicles, guidance, navigation and control, autonomy, overview |
| [33] | Review of ship safety domains: models and applications | Ship domain, collision avoidance, collision risk, maritime traffic engineering |
| [34] | Optimal path planning of unmanned surface vehicles | Optimisation, path planning, swarm, unmanned surface vehicles |
| [35] | Ship collision avoidance methods: State-of-the-art | Collision avoidance, conflict detection, conflict resolution, human-machine interactions, autonomous surface vehicle, manned and unmanned ships |

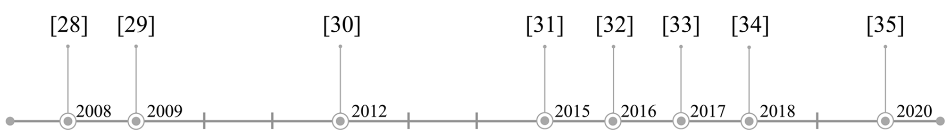


**Fig. 7** Timeline of other review papers

– *Path smoothing* is a process that receives a sequence of generated waypoints as input and connects them in an optimal way taking into consideration the limited curvature or turning radius of a vessel, where a smoothed path is obtained as a result.

A shortcoming with the above definitions, with path planning defined as being purely geometrical (spatial), is the question of how to define planning for moving obstacles and non-static wind or current forces. Thus, it may be argued that path planning should instead be defined as a spatiotemporal task, or one may adopt the term *dynamic path planning* for distinction.

## 2.4 Other literature reviews

In recent years, several survey papers have been published reviewing the path planning and collision avoidance of both ASVs and USVs and their components. The intention of the literature review presented in this paper is to further study and consolidate the current state-of-the-art of path planning and collision avoidance algorithms for ASVs. A selection of the most relevant papers for the period 2008–2020 is given in Table 1, with a corresponding timeline shown in Fig. 7. We summarise the selected papers in the following.

*Statheros et al.* [28], *2008*. The authors review the collision avoidance techniques and International Regulations for Preventing Collisions at Sea (COLREGs) [36] (see Sect. 3.2) for autonomous ships along three axes: mathematical models, soft computing (evolutionary algorithms, fuzzy logic, expert systems, and neural networks), and hybrid systems. The authors conclude that the hybrid systems look very promising for a ship's autonomous navigation, although it is challenging to harmonically merge different artificial intelligence (AI) technologies together.

*Tam et al.* [29], *2009*. The authors review past studies on collision avoidance and path planning of autonomous ships up until the year 2008. The reviewed papers are organised on a timeline in the sequence of their publishing date, setting focus on the evolution of algorithms. Some of these papers are also categorised according to their point of focus; earlier papers typically focus more on collision avoidance, whereas more recent papers focus more on path planning. The limitations of previously developed algorithms highlighted by the authors include: (a) the lack of environmental factors in algorithms, (b) working with only semi-dynamic obstacles (rather than true dynamic obstacles), (c) having idealised ship dynamic models, and (d) lack of compliance to COLREGs in many cases.

*Campbell et al.* [30], *2012*. The authors focus on AI solutions for autonomous ships. The review discusses the current state of USV collision avoidance research and reveals weaknesses in obstacle detection and avoidance (ODA) systems found in the literature. The review also inspects the integration of COLREGs for the general case and for multiple unmanned vessels in cooperation within the obstacle avoidance protocols.

*Zeng et al.* [31], *2015*. Whereas the other review papers we have selected to include in this section are related to ASVs, we have chosen to include one review by Zeng et al. [31], who present a set of recently developed AUVs and provide a detailed literature review of their operational endurance and specifications. The review paper sheds light on path planning and optimisation techniques from the angle of their performance aspects (safety, energy consumption, voyage time), aiming to highlight challenges that need to be addressed to achieve higher levels of autonomy.

*Liu et al.* [32], *2016*. This paper reviews all three components of GNC for USVs. The authors offer a classification of existing GNC approaches using various criteria where only a part of the research is dedicated to path planning and collision avoidance. The review is accompanied by several comprehensive figures summarising common challenges and the history of the development of USVs, listing advantages and limitations of the used sensors with great focus on classifying the control methods.

*Szlapczynski and Szlapczynska* [33], *2017*. The authors discuss a number of ship safety domain models that are a part of the autonomous ship collision avoidance system. The paper emphasises that the factors considered in different safety domain models are usually more important than the shape of the domain itself. However, to enable real-time systems operation, mostly single parameters such as the time to the closest point of approach (TCPA) and/or the distance to the closest point of approach (DCPA) are used instead of the whole ship safety domain.

*Singh* [34], *2018*. This review paper provides an overview of components of optimal local and global path planning for USVs, considering compliance with COLREGs and different objective functions of both vessels in formations and single vessels.

*Huang et al.* [35], *2020*. This paper reviews collision prevention techniques both for manned and unmanned ships, distinguishing three modules, namely, motion prediction, conflict detection, and conflict resolution. The paper identifies up-to-date drawbacks and trends in the field as well as reviews and compares the existing collision avoidance methods based on properties proposed by authors.

*Remarks on literature reviews.* The analysis of previous reviews shows that in recent years, there has been a growing interest in path planning and collision avoidance problem for ASVs. While authors of the analysed reviews are referring to both ASV and USV type of surface vessels, the algorithms used in both cases remain similar. The same applies to the reviewed algorithms for AUVs by Zeng et al. [31] that can be adapted for use for ASVs.

## 3 Regulatory framework

Increased interest in autonomous marine transport has led to the development of guidelines and safety conventions. Guidelines describe both autonomy levels and trial guidelines for maritime autonomous surface ships (MASS). To our knowledge, design standards for ASVs have not yet been developed.

### 3.1 Levels of autonomy

Current guidelines for autonomy levels define and clarify the concept of different levels of ship autonomy to make it understandable for all involved parties. In 2014, the Society of Automotive Engineers (SAE) first developed the guidelines that explain six levels of autonomy for cars, ranging from cars with manual control to fully autonomous cars [37]. Similarly, in 2016, Lloyd's Register (LR) proposed six

**Table 2** Levels of vessel autonomy according to Lloyd's Register [38]

| Level | Description |
|---|---|
| AL0 | No automation functions, manual navigation of a ship |
| AL1 | On-ship decision support system, data available to crew |
| AL2 | Off-ship decision support system, shore monitoring |
| AL3 | Semi-autonomous ship with active human in-the-loop where crew can intervene |
| AL4 | Human-on-the-loop, ship operates autonomously with human supervision |
| AL5 | Fully autonomous ship with means of human control |
| AL6 | Fully autonomous ship without need for any human intervention |

**Table 3** Levels of vessel autonomy according to NFSA [39]

| Level | Description |
|---|---|
| Level 1 | Decision support system |
| Level 2 | Automatic ship |
| Level 3 | Constrained autonomous ship |
| Level 4 | Fully autonomous ship |

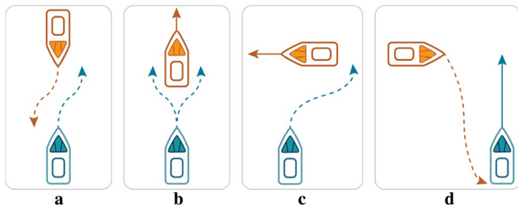

**Fig. 8** Four encounter situations of power-driven vessels according to the COLREGs rules 13–15: (**a**) head-on, (**b**) overtaking, (**c**) crossing from the right (starboard) and (**d**) crossing from the left (port). The bottom (blue) vessel is the own vessel and the top (orange) is the target vessel. Solid (dashed) line indicates stay-on (give-way) action

autonomy levels (ALs) for ships [38], ranging from manually navigated ships at autonomy level AL0 to fully autonomous ships at autonomy level AL6, which are summarised in Table 2. Throughout this paper, the term ASV is used to refer to both levels AL5 and AL6, whereas the term USV refers to the level AL4.

LR is not the only organisation that has defined levels of autonomy for surface vessels. Norwegian Forum for Autonomous Ships (NFAS) categorises surface vessels into four groups according to their level of autonomy [39], as shown in Table 3. More detailed descriptions of the division of ships based on both autonomy and manning levels can be found in Rødseth and Nordahl [39].

We note that although one might think that simple remote control could be the first step towards autonomy, the above indicates that increasing the level of automation is the appropriate way forward. In the case of simple remote control, the need for high and expensive communication bandwidth (cameras and radar) and risk of loss of communications are good arguments against remote control before the vessel has reached a high level of autonomy. Likewise, simple remote control would probably not reduce the amount of staff, just moving them to shore.

### 3.2 Safety regulations

A crucial aspect of ASVs is safety and the ability to safely navigate in open waters, coastal areas, and congested waters like harbours. Clearly, the safety issue is the most challenging when avoiding collisions with other dynamic vessels or land in high-traffic congested waters.

There are several regulations that consider the safety of surface vessels. One of them is the International Convention for the Safety of Life at Sea (SOLAS) [40], proposed by the International Maritime Organization (IMO) in 1974, that sets safety standards in the construction, equipment and operation of merchant ships. Another regulation, COLREGs, was proposed by IMO in 1972 in an attempt to define how vessels should act in various situations when meeting other vessels to navigate through waters safely and without collisions [36]. These regulations, which were developed for manned surface vessels, need to be taken into account when developing path planning and collision avoidance systems for ASVs even though there might be some exceptional cases.

COLREGs consist of 38 rules that are categorised into 5 parts. Part B "Steering and Sailing rules," which contains 16 rules, is responsible for handling collision avoidance situations. When evaluating risk of collision, it is necessary to follow Rule 7 using on-board measurement devices (compass, radar) to ensure safe navigation. In situations when the risk of collision exists, proper actions to avoid collisions are determined by Rule 8. Four different two-vessel encounter situations of power-driven vessels—overtaking, head-on situation, and crossing from the port side or starboard side—are described by COLREG rules, as illustrated in Fig. 8. These actions are true in the encounter situations when both vessels are in sight of one other and a risk of collision (Rule 7) is formed. In these situations, alteration of course is chosen over alteration of speed. To have a better understanding of the actions taken by give-way and stand-on vessels in the

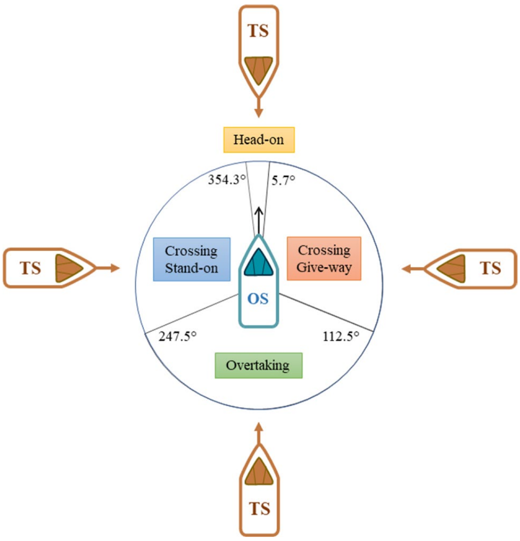


**Fig. 9** Categorisation of collision avoidance actions based on COLREGs that need to be taken depending on the angle of the approaching target ship (TS) in relation to own ship (OS)

encounter situations, it is also important to consider Rule 16, explaining actions taken by give-way vessel, and Rule 17, explaining actions of stand-on vessel Deciding when to take which action from the own vessel's perspective depends on the relative bearing of the approaching target vessel, which must be avoided, as illustrated in Fig. 9. However, an exceptional situation may occur, defined by Rule 17, when it is apparent that the give-way vessel does not take the necessary collision avoidance actions. In this case, the stand-on vessel, instead of keeping its course and speed, must take actions to avoid possible danger situations.

However, there are also a few special cases of collision avoidance: when at least one of the vessels at the encounter is a sailing vessel (Rule 12), and when there is a situation of restricted visibility (Rule 19). Responsibilities between different types of vessels while navigating are covered by Rule 18. The implementation of this rule requires a good situational awareness, for being able to differ between vessels engaged in fishing, sailing vessels, and vessels not under command. COLREGs also acknowledge situations when it is allowed to violate the collision avoidance rules (Rule 2(b)). The rule states that, in immediate danger situations, it is necessary to follow ordinary practice of seamen to take required precautions to avoid fatalities. While performing manoeuvre, limitations of both vessels must be considered.

Finally, the latest newcomer to the set of regulations is Interim Guidelines for MASS Trials [41] proposed by IMO in June 2019. These guidelines have been developed with the goal to ensure that the trials of autonomous ships are "conducted safely, securely and with due regard for protection of the environment." Although these guidelines might be general, without going very deep into details, and be in their first stage of the development, they are a good starting point to regulate trials of ASVs in the future.

## 4 Guidance, navigation and control

### 4.1 GNC architecture

According to Fossen [42], a marine vessel's control system consists of three main modules—the GNC components. These are generally constituted by onboard computers and software, which together are responsible for managing the entire ASV system, which is why they are considered as some of the most vital components of the ASV. An alternative way of organising the architecture of the control system is proposed by Lekkas [25], who defines a path planning module separately from the guidance layer in the GNC system, hence having four main modules.

In an attempt of reconciliation, we propose an architecture that includes many components from several of these variations (see Fig. 10):

*The guidance module.* This module generates a path that the vessel will follow to accomplish its mission starting from the vehicle's current position to a designated end position. The guidance module receives information about the environment and the own vessel's state as an input from the navigation module. It is then responsible for continuously generating and updating desirable paths (feasible, safe, optimal, and smooth are common criteria) to the control system according to the information provided by the navigation system, assigned missions, vehicle's capability, and environmental conditions. The resultant path that is transmitted to the control module can be represented as a set of waypoints. In the case of applying a path smoothing technique on the set of the resulting waypoints, the output that is transmitted to the control layer is a smoothed path that needs to be followed.

*The navigation module.* This module is responsible, first, for estimating the own vessel's state, e.g., determining the location of the vessel and state parameters like position, velocity, and attitude. Second, it includes perceiving information about the environment and surroundings. The obtained data can be fused to provide the vessel with necessary information about situational awareness and for providing the guidance system with the necessary inputs.

*The control module.* This module determines the necessary control forces for a vessel to follow the path that is set by the guidance system, considering the current state of the vessel determined by the navigation system. The input of the

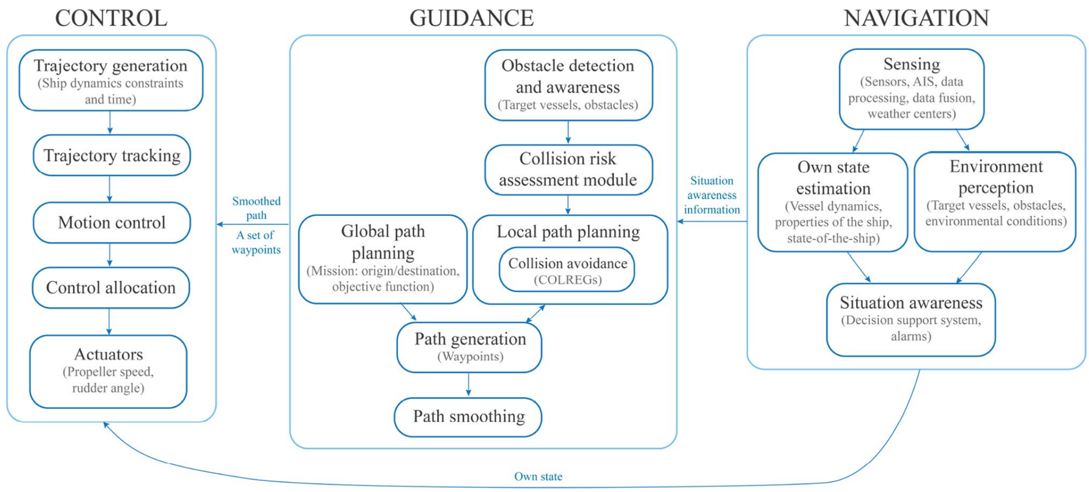


**Fig. 10** Proposed GNC architecture

control module can vary from an already smoothed path to a simple set of waypoints that need to be followed. The control module needs to make sure that the resulting path is feasible with regards to the vessel's control limitations. One of its main responsibilities is the minimised-error trajectory tracking by setting the correct control commands to the actuators (e.g., propeller speed and rudder angle).

*Remarks on GNC modules.* The architecture proposed above is not strictly defined as the ultimate and 'one and only' architecture of control systems for ASVs. Rather, it represents our preferred means for studying path planning and collision avoidance within GNC. Contrary to Lekkas and Fossen [43], we define the role of path planning and collision avoidance to be a part of the guidance module (layer). The following subsection extensively describes path planning and collision avoidance components and their role in the guidance module.

### 4.2 Path planning and collision avoidance

The literature review shows that in most of the papers the two distinguished types of path planning are *global path planning* and *local path planning*, e.g., Polvara et al. [44], Wang et al. [45], Xie et al. [46]. Global (deliberative) path planning finds a safe path from the initial state to the goal state considering known obstacles and assuming that a complete model of the environment is available. On the other hand, local (reactive) path planning, uses the information about the local environment around the vessel taking into consideration information from the sensors for situational awareness and putting emphasis on avoiding the dynamic obstacles in the vicinity to generate a feasible and safe path.

The actions of a local path planner can result in a deviation from the previously planned path or a change in speed. For local path planning, in particular, it is important to follow COLREGs, unless exceptional situations occur, in order to safely avoid all of the obstacles. However, when an ASV should follow COLREGs and when it should not, remains an open question. Also, both local and global path planning modules might not be necessarily separate components; some of the algorithms are performing overlapping tasks.

On the other hand, there is also a different variation of suggested planning levels, used by some authors [47–49]: *high-level global path planning*, which creates paths avoiding known static obstacles; *mid-level protocol-based COLAV*, which follows a set of rules (like COLREGs); and *low-level reactive COLAV*, which avoids immediate collisions in close range, without considering COLREGs.

In some cases, to ensure the feasibility of a path and reproduce the manned vessel's behaviour, it is necessary to apply path smoothing methods over the generated linearly connected path. According to Lekkas et al. [50], there are two main categories of paths resulting from connecting waypoints: (1) a combination of straight line and arc segments, and (2) splines. A comprehensive description of these path categories can be found in LaValle [24], and Lekkas and Fossen [51].

## 5 Classification of path planning algorithms

Emerging from robotics, path planning is a developing research field applied to ground vehicles, underwater vehicles, surface vessels, and drones, with many algorithms

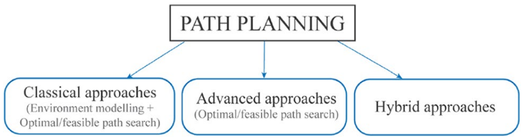


**Fig. 11** Path planning approaches

being reused and adapted for each of these contexts. There are clearly similarities between autonomous vehicles navigating on unstructured roads without driving lanes (parking, intersections, diversions, complete road blockage, unorganised traffic, etc.) and open sea manoeuvring of ASVs. However, finding an optimal safe path while driving in a lane can often be simpler than on unstructured roads or open areas where the distribution of obstacles is irregular. The complexity of the environment and kinodynamics makes path planning of surface vessels more challenging and different from ground vehicles.

Collision avoidance includes multiple issues that have to be solved, such as dealing with external disturbances (wind, waves, current); modelling the own ship dynamics; predicting the behaviour of target vessels (vessels that must be avoided); avoiding close-range collisions, grounding, and stranding; docking; and safety.

For collision-free path planning, in addition to the above, finding the optimal path, smoothing the followed path, evaluating the path efficiency, ensuring path following, and so on must be solved.

In this section, we present and categorise path planning algorithms used for ASVs.

### 5.1 Path planning algorithms

We have adopted a general categorisation of path planning algorithms based on Souissi et al. [52], and suggest that such algorithms can take a *classical* approach, an *advanced* approach, or a *hybrid* approach (see Fig. 11).

*The classical approach.* This approach is a two-step process consisting of (1) environment modelling to prepare for the search; and (2) performing the search of the optimal path in this environment. These methods are most commonly used for global off-line path planning with static obstacles where there is no need for path replanning or local collision avoidance [34, 52].

First, for the environment modelling, there are two main approaches used, based on [52] (see Figure 12):

– *Roadmap-based methods* which attempt to capture the free-space connectivity with a graph. Their main goal is to reduce the N-dimensional configuration space to a set of one-dimensional paths, which are then searched, e.g., visibility graphs and Voronoi diagrams [53].
– *Cell decomposition methods* that decompose the configuration space of the problem into nonoverlapping convex regions referred to as cells [54]. After the decomposition has been performed, a connectivity graph, representing the adjacency relationships of the cells, is created. The decomposition components can be both regular and irregular grids as well as a navigation mesh [52].

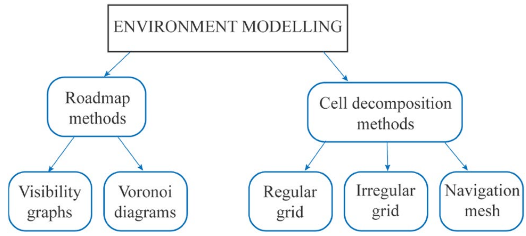


**Fig. 12** Methods used for environment modelling in the classical approach

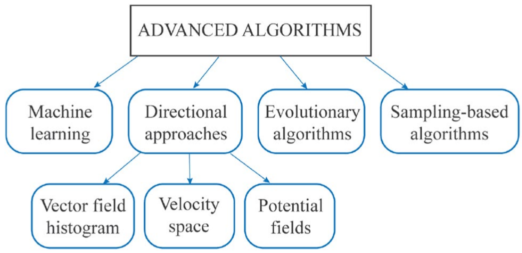


**Fig. 13** Classification of the algorithms using an advanced approach

We note, however, that these two main approaches may imply static environmental conditions, and as such may require further refinement to capture the time-varying nature of the environment, effectively adding another dimension to the state space.

After modelling of the environment, the roadmap or connectivity graph is searched for a collision-free path between the initial and the goal positions.

*Advanced approach.* These algorithms are commonly used to deal with dynamic obstacles, path re-planning and local collision avoidance in real time. Most often, they do not require environmental modelling beforehand. Based on the literature review, we propose the following classification of the advanced approaches used in the path planning for surface vessels' (see Fig. 13):

- *Machine learning algorithms*, which has attracted the attention of some researchers. In Cheng and Zhang [55], the authors proposed a concise deep reinforcement learning obstacle avoidance (CDRLOA) algorithm using an avoidance reward function and decision-making module. This algorithm proves its efficiency in complex navigation situations and unknown environment disturbances.
- *Directional approaches*, which include three kinds of methods [56]:
  - *potential field methods*, which are most often used due to low computational load requirement for trajectory generation. An attractive field is assigned to the target, whilst negative fields represent obstacles and so the vessel is repelled at these locations. In general, the trajectory can be generated effectively in real time and planning and control are merged into one function, however, a disadvantage is the risk of being trapped in local minima [57].
  - *velocity space methods*, for which, we define three sub-categories: velocity obstacles [58], dynamic window [45] and curvature velocity.
  - *vector field histogram methods,* which use histogram grids to plan motion in real time, taking into account the dynamics and shape of the vessel, e.g. a polar histogram [29].
- *Evolutionary algorithms* (EAs), which represent AI by mimicking the evolutionary behaviour of biological systems. They address the problem of multi-objective optimization where traditional optimization methods such as gradient descent become too complex or computationally demanding. However, the disadvantage of some of them is once again the potential of getting trapped in local minima, finding at best a near-optimal solution (as the global optimum is never guaranteed) or even failing to find a solution at all in some instances. EAs such as particle swarm optimization (PSO) [59], ant colony optimization (ACO) [60], genetic algorithm (GA) [61], wolf colony algorithm (WCA) [62], bio-inspired neural networks, and other algorithms have all been used and implemented for solving the path planning problem of ASVs.
- *Sampling-based algorithms* have been shown to work well in practice and possess theoretical guarantees such as probabilistic completeness [63]. The probabilistic roadmap (PRM) and rapidly exploring random tree (RRT) [64] algorithms and their variations are some of the most often used algorithms.

*Hybrid approach.* In this context, these algorithms are ones that combine several path planning algorithms to ensure safe and feasible navigation both globally and locally. Whilst these algorithms are often more complicated, the result is often better than when the combined methods are applied separately, as in many cases they overcome each other's drawbacks. Some good examples are presented by Zhou et al. [65], Wang et al. [45], Xiong et al. [66], Blaich et al. [67].

## 6 Discussion

The increased popularity of ASVs is clearly evidenced by the several attempts of shipbuilding companies to introduce autonomy at sea and the success of these projects. Based on the industry's predictions, fully autonomous surface vehicles are expected by 2025. A positive reinforcement here is the multiple collaboration projects between companies that lead to knowledge sharing and faster development of the technology.

Although we have tried to elucidate the terminology of the path planning and types of surface vessels in this paper, the confusion of terms used in the literature still remains and should be addressed also in the future. The confusion of the terms 'ASV' and 'USV' can be partially explained by the vague and unclear boundary between the levels of autonomy and manning onboard. It needs to be emphasised that even fully autonomous operational surface vessels might have passengers and/or staff working onboard and therefore should be categorised as manned. Additionally, the issue that is not raised in most of the papers up to date is whether remote control is the right first step towards full autonomy of surface vessels. As we already discussed in Sect. 3, a remotely controlled USV that does not have full operational autonomy as a back-up plan is at high risk due to the potential of loss of communication, which could be disastrous and lead to total loss of control of the ship.

Another topic for discussion is safety conventions like COLREGs. These regulations, first developed in 1972, were clearly developed for human-controlled manned vessels. Thus, in an era where control over vessels is deliberately transferred to computers, the open question is how well are ASVs going to follow rules written for human beings. Furthermore, it is possible to envision exceptional situations when an ASV should not follow the defined collision avoidance rules to avoid last-minute collision. Therefore, it is clear that the COLREGs Rule 2(b) should be implemented in the GNC system of an ASV. The question of when to follow regulations and when not to is a topic of future research. Alternatively, an improved version of these regulations should be developed to account for both USVs, ASVs and traditionally manned surface vessels on waters.

To summarise research about path planning algorithms for ASVs, there is a wide variety of different methods for path planning that have already been successfully applied for USV or ASV applications. Moreover, some of the non-applied path planning algorithms that have been implemented for ground vehicles navigating on the unstructured roads or AUVs can likely be adapted for ASVs too.

From a path planning and collision avoidance perspective, we have proposed just one scheme for classification of path planning algorithms and models of GNC, hopefully positively complementing other schemes and views in the literature. Several elements of our study could have been analysed further in-depth, including collision avoidance methods, path following, and path smoothing methods but have been left out to limit the scope of this paper. We do, however, cover these topics in our accompanying paper [3].

## 7 Conclusions

We have given an overview of the current situation in the field of path planning and collision avoidance of ASVs by explaining important aspects such as autonomy, safety, and GNC system architecture from a path planning and collision avoidance point of view. Some inconsistencies within terminology in the literature have been highlighted, and regulations related to path planning and collision avoidance of ASVs have been analysed and discussed. Our review paper contributes to a rapidly growing field that still contains many unanswered questions. We acknowledge that ASVs have not only great potential but also a number of challenges that must be considered and treated with caution in the years to come.

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REVIEW ARTICLE

# Path planning and collision avoidance for autonomous surface vehicles II: a comparative study of algorithms

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**Abstract**
Artificial intelligence is an enabling technology for autonomous surface vehicles, with methods such as evolutionary algorithms, artificial potential fields, fast marching methods, and many others becoming increasingly popular for solving problems such as path planning and collision avoidance. However, there currently is no unified way to evaluate the performance of different algorithms, for example with regard to safety or risk. This paper is a step in that direction and offers a comparative study of current state-of-the art path planning and collision avoidance algorithms for autonomous surface vehicles. Across 45 selected papers, we compare important performance properties of the proposed algorithms related to the vessel and the environment it is operating in. We also analyse how safety is incorporated, and what components constitute the objective function in these algorithms. Finally, we focus on comparing advantages and limitations of the 45 analysed papers. A key finding is the need for a unified platform for evaluating and comparing the performance of algorithms under a large set of possible real-world scenarios.

**Keywords** Autonomous surface vehicle (ASV) · Path planning · Collision avoidance · Algorithms · Safety

## 1 Introduction

There is growing appeal for autonomous systems in multiple fields, including manufacturing, transportation, routine work, and work in dangerous environments. In the wake of progress in the domain of autonomous cars, much attention is also given to autonomous surface vehicles (ASVs). In an accompanying article in this journal [1], we present a review on theory and methods for path planning and collision avoidance of ASVs. We attempt to unify and clarify relevant terminology and concepts such as autonomy and safety, as well as models for guidance, navigation, and control. Moreover, we propose a classification scheme for distinguishing and comparing algorithms for path planning and collision avoidance.

Here, we extend this scheme to classify state-of-the-art algorithms presented in 45 different peer-reviewed scientific papers. Several kinds of algorithms are covered, including evolutionary algorithms, sampling-based algorithms, cell decomposition methods, directional approaches, and roadmap methods. We have also included some algorithms for unmanned surface vehicles (USVs).

As for any literature review paper, it is impossible to cover everything in the literature within the scope of a single paper. The number of papers studied before arriving at the shortlist of the 45 papers presented here is probably in the ballpark of several hundreds. We have carefully selected papers that we ultimately found useful to include.

Moreover, whereas much of what we present is general across vessel size, other considerations will differ whether the vessel is a small boat or a large ship. In such cases, the reader should note that larger ships are our main focus. Likewise, although some elements of path planning and collision avoidance are common across congested waters and open sea, we are mainly concerned with shorter time frames and congested waters in the papers we study here.

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**Table 1** Timeline of the first time use of dominating algorithms for USV/ASV guidance applications

| Year | Algorithm | References |
|---|---|---|
| 1999 | Genetic algorithm (GA) | [2] |
| 2001 | Fuzzy logic | [3] |
| 2008 | A* | [4] |
| 2008 | Rapidly-exploring random tree (RRT) | [4] |
| 2010 | Ant colony optimization (ACO) | [5] |
| 2012 | Particle swarm optimization (PSO) | [6] |
| 2012 | Dijkstra | [7] |
| 2013 | Voronoi diagram | [8] |
| 2014 | Velocity obstacles (VO) | [9] |
| 2015 | Artificial potential field (APF) | [10] |
| 2015 | Fast marching method (FMM) | [11] |
| 2018 | Deep reinforcement learning (DRL) | [12] |

The rest of the paper is organised as follows: Sect. 2 provides a timeline of some of the most influential algorithms for path planning and collision avoidance for ASVs or USVs. Section 3 extracts distinguishing properties of the algorithms from the literature, and analyses and compares papers based on these properties. Section 4 analyses the proposed algorithms based on their properties whilst focusing mainly on two aspects: (1) safety and collision risk assessment (CRA), and (2) choice of objective function. Section 5 extracts the advantages and limitations of the algorithms used in the different papers. Finally, Sect. 6 presents a discussion, whilst some concluding remarks are drawn in Sect. 7.

## 2 Timeline of algorithms

The first use of some of the most influential algorithms used for path planning and collision avoidance for ASVs or USVs is shown in Table 1. Notably, these algorithms have also been successfully used at earlier times for guidance of autonomous underwater vehicles (AUVs), unmanned aerial vehicles (UAVs), or autonomous ground vehicles (AGVs). Note that Table 1 is by no means an exhaustive list but highlights some dominating algorithms that have been commonly employed, directly or in some derivative form, or in combination with others.

## 3 Properties of algorithms

Although some algorithms in the literature clearly separate the tasks of path planning and collision avoidance, others do not, and attempt to solve both problems with overlapping modules [1]. Furthermore, it is generally not easy to compare path planning and collision avoidance algorithms for ASVs due to the variety of constraints and objectives that exist. One example is the use of regulations such as the International Regulations for Preventing Collisions at Sea (COLREGs) [13]: whereas some algorithms successfully generate paths for avoiding obstacles whilst simultaneously obeying several COLREG Rules [e.g., 14–18], others fully or partially ignore these regulations [e.g., 11, 19, 20–22]. For adoption in the future, fully autonomous surface vessels must comply with all the rules of COLREGs. We appreciate, however, that algorithms that comply only with a subset of COLREGs are still a step towards this goal and a contribution towards full COLREGs compliance in the future.

The literature analysis in Vagale et al. [1] shows that there are several properties of path planning and collision avoidance algorithms that can be used for classification and analysis of the algorithms:

- *Compliance with COLREGs*: partial/full consideration of COLREGs for collision avoidance.
- *Environmental disturbances*: taking into account wind, waves, currents, and tides.
- *Planning type*: global and/or local planning.
- *Obstacle type*: whether a vessel can deal with static and/or dynamic obstacles (including single or multiple encounter situations at the same time).
- *Environment type*: discrete or continuous environment.
- *Type of avoidance action*: course change or speed change, or a combination of both.
- *Testing of algorithm*: simulation or field test.
- *Traffic category*: congested waters (areas crowded with static/dynamic obstacles, including harbour areas, lead to low own vessel speed), open waters (minimal number of static and dynamic obstacles, lead to high own vessel speed), riverines (manoeuvring is limited, current is present), and coastal areas (mostly static obstacles, such as land, islands, and shallow water, lead to varying speed).
- *Predictability of environment*: known or unknown environment.
- *Planning time*: real-time (online) or offline.
- *Control horizon*: infinite or receding horizon control.
- *Number of encountered obstacles*: single or multiple target vessel encounter situations.
- *Vessel dynamics and kinematics*: maximum ship turning rate, maximum vessel speed, other vessel's motion constraints, torque of the vessel, etc.
- *Subject of research*: type of the researched vessel or system [ASV, USV, and decision support system (DSS)].
- *Safe zones*: safety margin, virtual safety zone, ship domain, ship arena, or circle-of-rejection, around the own vessel or static/dynamic obstacles.

Note that Tsou and Hsueh [5] define ship domain as "the sea around a ship that the navigator would like to keep free of other ships and fixed objects." This criterion has been widely used in ships' collision avoidance, marine traffic simulation, calculation of encounter rates, vehicle tracking system (VTS) design, and so forth. It differs from ship arena, which is a bigger area around the vessel used to determine the time of taking collision avoidance actions [23]. Similarly, a safety zone can be assumed around each obstacle instead of the own ship, called the circle-of-rejection (COR) [24].

Based on the aforementioned properties, eight properties have been chosen for a comparative study of 45 papers containing algorithms for path planning and collision avoidance of ASVs (see Table 2). The choice of these eight properties is based on the most common available, and relevant, information in algorithm descriptions. Some other properties were neglected due to many papers excluding the very same information regarding such properties. The proposed comparison is an attempt to analyse these state-of-the art algorithms and benchmark them using the proposed criteria. Table 3 compares the ship- and environment-related properties across the chosen papers. The algorithms in the comparison of Table 3 are grouped in three groups, separated by white space, based on the "planning type" property. Each row of the table includes the paper reference ('Ref.'), the type of path planning, and/or collision avoidance algorithm(s) employed, followed by an analysis of how the 8 properties in Table 2 are taken into account.

Although the focus of this study is on methods for ASVs, papers related to USVs are also considered. The databases used for finding journal and conference papers were IEEE Xplore Digital Library and ScienceDirect. Additionally, the NTNU library was consulted using the search tool Oria, as well as suggestions from the reference organisation tool Mendeley. The keywords used for search were "ASV," "USV," "autonomous ships," "path planning," "collision avoidance," and "guidance." The papers included in the comparison are from the years 2010–2020, and the language was limited to English. The distribution of the analysed papers over the years is represented in Fig. 1. The number of papers with respect to each of the eight selected properties is represented graphically in Fig. 2.

We discuss each of the eight properties P1–P8 in turn, before making some general observations, mainly with reference to Table 3 and Fig. 2.

*P1. Planning type:* The analysis of the selected papers shows that 13 (29%) of the examined algorithms perform global planning and, hence, are mainly concerned with path planning; 17 (38%) algorithms perform local planning and collision avoidance; and 15 (33%) algorithms perform both global and local planning. We also found that in most of the cases, local planning is performed in real time, whereas global planning is often performed offline, prior to departure. In the hybrid cases, when both local and global planning is used, the algorithm is generally a combination of both real-time and offline planning and covers both path planning and collision avoidance. Hence, with this close correlation between local/real-time planning and global/offline planning, a separate property of the algorithm being real time or offline is not considered necessary in Table 3.

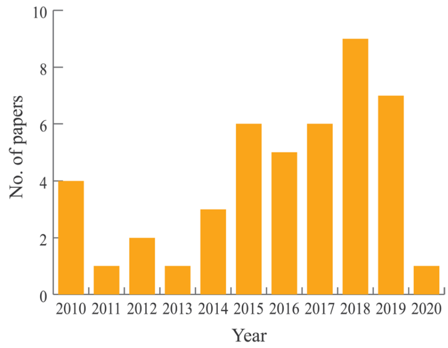


**Fig. 1** Annual distribution of the papers

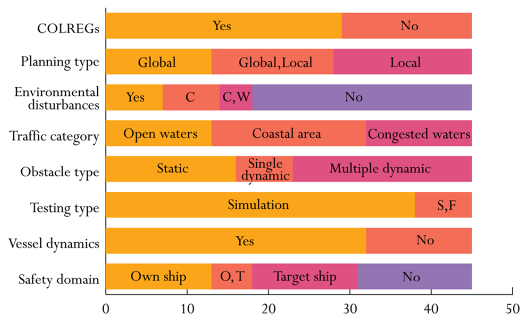


**Fig. 2** Distribution of properties among the papers

*P2. COLREGs:* The comparison table shows that compliance with COLREGs is included only in the path planning approaches that consider local path planning and collision avoidance (algorithms with property GL and L). Most often, algorithms take into consideration only up to four of the main encounter situations, described in the three COLREG Rules 13–15 [e.g., 40, 54]. These rules are usually implemented as constraints in algorithms and indicate which collision avoidance scenario should be used in the current situation. Eriksen et al. [41], on the other hand, have implemented a cost function penalising gentle turns and small speed changes for obeying COLREG Rule 8, which states that "action taken to avoid collision should be positive, obvious and made in good time." Hence, the ASV's behaviour should be obvious and makes sense to human captains.

**Table 2** Selection of algorithm properties

| # | Property | Categories |
|---|---|---|
| P1 | Planning type | Local (L), global (G), both (GL) |
| P2 | Compliance with COLREGs | Yes, no |
| P3 | Traffic category | Open waters (OW), coastal area (CA), congested waters (CW) |
| P4 | Obstacle type | Static (S), single dynamic (D1), multiple dynamic (Dn) |
| P5 | Testing type | Simulation (S), field test (F) |
| P6 | Consideration of environmental disturbance | Current (C), wind (Wn), waves (Wv), existing but unknown (Unk), no |
| P7 | Consideration of vessel dynamics | Yes, no |
| P8 | Presence of safety domain | Vessel safety domain (O), target vessel/obstacles safety domain (T), no |

Szlapczynski [39] has proposed an extended method that additionally focuses on COLREG Rule 19, planning the path in restricted visibility conditions. Johansen et al. [53] additionally have also implemented several other COLREG Rules, namely 8, 16, 17, and 18. These rules have been implemented as components of the cost function or as penalty functions. Some papers emphasise that, according to good seamanship practice, course change is preferred over speed change in collision avoidance scenarios [38, 49].

*P3. Traffic category:* Concerning the traffic categories considered in the papers, one part of the papers focuses on the "open waters" category (13 papers, or 29%), considering an area free from static obstacles such as land and islands. The same amount of papers are dealing with "congested waters" category (13 papers, or 29%) where the traffic most often is busy, such as harbour areas, where both multiple dynamic obstacles and static obstacles are present. However, most of the papers are considering the "coastal area" type of environment/traffic (19 papers, or 42%), where the environment is mostly cluttered with several static obstacles, but there is almost no presence of dynamic obstacles.

*P4. Obstacle type:* The analysed papers consider different types of obstacles. In the simplest cases, 16 (36%) of papers use algorithms that avoid only static obstacles, including land, islands, and underwater objects. Most of these algorithms are global path planning approaches. For dynamic obstacles, 29 (64%) of the papers consider moving target vessels, underwater vehicles, and icebergs, with 7 (16%) considering single dynamic obstacle situations and 22 (49%) considering more complicated situations involving avoidance of multiple dynamic obstacles. The high number of papers that focus on avoiding dynamic obstacles might be explained by the increased need for real-time collision avoidance solutions. The dynamic obstacle avoidance problem is more complicated, since knowledge of the target object movement is required, and therefore, the consideration of a time parameter must be included. In cases when there is no communication between the own vessel and the target vessels, the examined algorithms perform avoidance action by predicting future positions of target vessels. This can be done by assuming that the own vessel can observe and estimate the dynamics of the target object (velocity and course) and its size; inferring compliance with COLREGs; or by obtaining information from third parties, e.g., from Automatic Identification System (AIS) data.

*P5. Testing type:* Most of the papers, 38 (84%) in total, test the proposed algorithms only by means of simulations in a simulated test environment built for this reason, for example using simulation software and high-level programming languages such as MATLAB. The testing environment varies depending on the papers' objective, and may include the geographic area, traffic data, obstacles, and other parameters related to ship dynamics of both own and target vessels. Some papers perform tests in several scenarios for representing the flexibility of the algorithm adapting to different situations. Sometimes, the performance of an algorithm is compared with some other under the same environment. A common practice is to use real map data for simulations [e.g., 33, 35–38]. The remaining 7 (16%) papers are verified in both field tests and simulations. In these cases, small vessels, equipped with GNC systems, e.g., Springer USV [31, 24] and ARCIMS USV [48], are used. An outstanding project with thorough testing is represented in Varas et al. [48] where tests have been performed both on desktop simulations, on a bridge simulator, and on sea trials using a USV. In this paper, testing is performed using Monte Carlo simulations to detect weaknesses of the proposed method and using historical collision incident data for more realistic scenarios.

*P6. Environmental disturbances:* Table 3 shows that when it comes to environmental disturbances, more than half (27, or 60%) of the papers do not take any environmental disturbances into consideration. Several papers [e.g., 25, 26, 27] are focusing only on the effect of current on the vessel (7, or 16%), some consider both current and wind (4, or 9%) [47, 49, 53, 54], and only two papers consider both current, wind, and waves [29, 35]. None of the papers consider waves as the only environmental disturbance affecting the ship's movement; however, waves are included in two papers together with wind and current.

**Table 3** Comparison of situation/environment and ship-related properties of different algorithms in 45 selected papers

| Refs. | Algorithm | P1 | P2 | P3 | P4 | P5 | P6 | P7 | P8 |
|---|---|---|---|---|---|---|---|---|---|
| [25] | Voronoi-visibility algorithm | G | No | CA | S | S | C | No | T |
| [26] | Multi-layered fast marching method | G | No | CA | S | S | C | No | T |
| [12] | Deep Q-networks | G | No | CA | S | S | Unk | Yes | O |
| [27] | Pseudospectral optimal control | G | No | CA | S | S | C | Yes | T |
| [28] | Deep deterministic policy gradient | G | No | CA | S | S | Unk | Yes | O |
| [29] | Improved quantum ACO | G | No | CA | S | S | C,Wn,Wv | Yes | T |
| [30] | Q-learning | G | No | CA | S | S | No | Yes | No |
| [31] | Angle-guidance FMS | G | No | CA | S | S,F | C | Yes | No |
| [32] | Smoothed A* | G | No | CA | S | S,F | No | Yes | No |
| [33] | Finite angle A* | G | No | CW | S | S | No | Yes | O |
| [19] | Ant colony optimisation | G | No | CW | S | S | Unk | Yes | No |
| [34] | A* on border grids | G | No | CW | S | S | No | No | No |
| [35] | Genetic algorithm | G | No | OW | S | S | C,Wn,Wv | Yes | No |
| [36] | A* post smoothed + DW | GL | No | CA | S | S | No | Yes | T |
| [22] | Shortcut Dijkstra + APF | GL | No | CA | S | S,F | No | Yes | T |
| [20] | APF-ACO+Multi-layer algorithm | GL | No | CA | S | S,F | C | Yes | O |
| [17] | Modified artificial potential fields | GL | Yes | CA | Dn | S | No | No | No |
| [14] | R-RA* | GL | Yes | CA | Dn | S | No | No | O |
| [37] | Voronoi diagram + Fermat's spiral | GL | Yes | CA | Dn | S | C | Yes | No |
| [38] | Hierarchical multi-objective PSO | GL | Yes | CA | Dn | S | Unk | Yes | no |
| [39] | Evolutionary algorithm | GL | Yes | CA | D1 | S | No | Yes | O |
| [16] | Fast marching square method | GL | Yes | CA | D1 | S | No | No | No |
| [24] | Direction priority sequential selection | GL | Yes | CA | D1 | S | No | Yes | T |
| [40] | COLREG-RRT | GL | Yes | CW | Dn | S | No | Yes | No |
| [21] | Bacteria foraging optimization | GL | Yes | CW | Dn | S | No | Yes | O,T |
| [41] | A* with OCP + MPC + BC-MPC | GL | Yes | CW | Dn | S | C | Yes | T |
| [42] | Path-guided hybrid APF | GL | Yes | CW | Dn | S | No | Yes | T |
| [43] | Adaptive wolf colony search | GL | Yes | OW | D1 | S | No | Yes | O |
| [44] | Artificial potential fields | L | Yes | CW | Dn | S | No | Yes | T |
| [45] | Deep reinforcement learning | L | Yes | CW | Dn | S | No | Yes | O,T |
| [46] | COLREGs-constrained APF | L | Yes | CW | Dn | S | No | Yes | O,T |
| [47] | Dynamic reciprocal velocity obstacles | L | Yes | CW | Dn | S | C,Wn | Yes | O,T |
| [48] | Multi-objective PSO | L | Yes | CW | Dn | S,F | Unk | Yes | O |
| [49] | Deep Q-learning | L | Yes | CW | Dn | S,F | C,Wn | Yes | O,T |
| [50] | Fuzzy relational products | L | yes | OW | Dn | S | no | no | T |
| [15] | Optimal reciprocal collision avoidance | L | Yes | OW | Dn | S | No | No | No |
| [5] | Ant colony optimisation | L | Yes | OW | Dn | S | No | No | O |
| [51] | Deterministic algorithm | L | Yes | OW | Dn | S | no | yes | no |
| [52] | Probabilistic obstacle handling + A* | L | Yes | OW | Dn | S | No | Yes | No |
| [53] | Model predictive control | L | Yes | OW | Dn | S | C,Wn | Yes | O |
| [54] | Evolutionary algorithm | L | Yes | OW | Dn | S | C,Wn | Yes | T |
| [9] | Velocity obstacles | L | Yes | OW | Dn | S,F | No | No | T |
| [55] | Fuzzy membership function | L | Yes | OW | D1 | S | No | No | O |
| [18] | Genetic algorithm | L | Yes | OW | D1 | S | No | No | O |
| [23] | NSGA-II | L | Yes | OW | D1 | S | No | No | O |
| | Sums of sub-properties | G: 13 | No: 16 | CA: 19 | S: 16 | S: 38 | C,Wn,Wv: 2 | Yes: 32 | O,T: 5 |
| | | GL: 15 | Yes: 29 | CW: 13 | Dn: 22 | S,F: 7 | C,Wn: 4 | No: 13 | O: 13 |
| | | L: 17 | | OW: 13 | D1: 7 | | C: 7 | | T: 13 |
| | | | | | | | Unk: 5 | | No: 14 |
| | | | | | | | No: 27 | | |

Out of all of the environmental disturbances, current is the most often included one (13 papers), followed by wind (6 papers) and waves (2 papers).

*P7. Vessel dynamics:* Vessel dynamics have been considered in most of the cases (32 papers, or 71%). Some of the ship's parameters included in the papers are dynamics of the vessel, a manoeuvring model, a kinetic model, turning ability, maximum steering angle or speed, and other vessel motion constraints or limitations. The remaining 13 papers (29%) do not consider vessel dynamics.

*P8. Safety domain:* To enhance safety, a safety zone (domain) is required for ensuring the respect of the closest area around the own vessel, target vessels, or obstacles. Across the applied algorithms, safety zones take a variety of shapes, including circle, ellipse, rectangle, shipshape, and inverted cone. An own ship domain has been implemented using various parameters in 13 (29%) papers. A safety domain around target vessels or a safety zone around obstacles has been implemented in the same number of papers (29%). Finally, 5 (11%) of the algorithms have implemented both an own ship domain and a domain, whereas 14 (31%) algorithms do not include a safety domain.

*Hybrid approaches:* The study shows that most of the algorithms are using a hybrid approach for path planning and collision avoidance that combines two or more methods to improve the performance and cover different sides of real-life situations. For example, Niu et al. [25] combine Voronoi diagram with visibility graph and Dijkstra's search, creating a hybrid Voronoi-visibility algorithm; Wu et al. [20] combine artificial potential field method with ACO algorithm for global planning and uses a multi-layer obstacle-avoidance framework for local planning; Xie et al. [22] combine Dijkstra's algorithm with APF method; and Candeloro et al. [37] merge Voronoi diagram with Fermat's spiral (FS) to ensure curvature-continuous paths. In most cases, the purpose of the hybrid approach is to be able to solve both local and global path planning.

*Single- vs. multiple-vessel control:* Most papers are focusing on single-vessel path planning methods, whereas a few authors are considering path planning of a formation or a fleet of more than one vessel [e.g., 16, 56–58]. Notably, for formation path planning in a static environment, conflicting collision avoidance situations between formation members also need to be considered, turning the environment into a dynamic one.

## 4 Safety and objective functions

A crucial aspect of ASVs is the ability to navigate safely in open waters, coastal areas, and congested waters like harbours. To achieve safe manoeuvring, multiple components should be considered, such as COLREGs, situational awareness (consideration of both dynamic and static obstacles), dynamic properties and limitations of the vessel, environmental disturbances, and safety domain [59]. One way of ensuring the safety of the own vessel considering the dynamic target vessels in the vicinity is to include some safety aspects when searching for collision-free paths, thus evaluating risk of collision. Hence, safety of the own and target vessels should be incorporated, or at least considered, when generating paths based on optimisation of an objective function.

In Fig. 3, we highlight what we have identified as being the four most often used safety components across the examined literature, namely (1) safety conventions, (2) collision risk assessment (CRA), (3) safety domain, and (4) environmental disturbances.

In the following subsections, however, we limit our study to analysing the employment of (1) collision risk assessment (CRA) and (2) objective function in the algorithms proposed in the selection of literature.

### 4.1 Collision risk assessment

CRA is one of the key factors that aids in evaluating the safety of the path to be taken. It is an assessment tool that may include several safety criteria based on the current and predicted situation, own or target vessels' parameters, and their mutual relationship.

An often used risk evaluation criterion for CRA in the literature is the closest point of approach (CPA), which can be measured both in time and distance, as illustrated in Fig. 4.

The CPA is the position at which two dynamically moving vessels will have the shortest distance between them at a specific time. The time to the closest point of approach (TCPA) is the time when this position is reached. The


**Fig. 3** Safety components

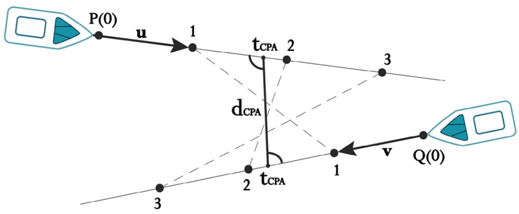


**Fig. 4** The concept of time and distance of CPA

distance of the closest point of approach (DCPA) is the distance between both CPA points on the trajectory of each vessel.

Both TCPA and DCPA are proposed for the maritime field by Kearon [60], and they are used mainly for collision risk assessment and navigation safety enhancement. The TCPA and DCPA parameters, however, have a drawback. As noted by the authors in Nguyen et al. [61], both parameters do not adequately represent the danger of a collision when moving into head-on situations and overtaking situations.

CRA parameters are not limited only to TCPA and DCPA, although these are the most commonly used ones. Other papers also consider parameters such as the distance of the last-minute avoidance, distance to the target vessel, ratio of speed, relative bearing, safe passage circle, and distance of adopt avoidance action [15, 47, 62].

## 4.2 Objective function

There are many possible criteria for path evaluation using an objective function. Some of the most often used criteria which we have identified are:

- *Path length*: length of the obtained path (either before or after smoothing of the path).
- *Voyage time*: time required to reach the target position when traversing the obtained path.
- *Smoothness*: connection of waypoints in an optimal way taking into consideration limited curvature or turning radius of the ship. This property partly reflects whether the path is feasible from the ship's perspective. Reduced number of sharp turns or a path smoothing module are some examples of a smoothness component.
- *Tractability*: the practicality of the path, especially in dynamic environments when some waypoints have to be relocated during the journey [63].
- *Energy consumption*: a criterion that might be influenced by several other factors, including path length, vessel's speed, or the effect of sea currents on the vessel, in terms of economy.
- *Path precision*: how precisely does the designed path pass through waypoints [63].

The comparison of (1) CRA components and (2) objective function criteria included in papers is presented in Table 4. Here, CRA analysis includes only the most often used criteria, namely TCPA and DCPA. The analysis of the objective function considers only the four most often implemented components: length, time, smoothness, and energy efficiency. For all columns, the presence/absence of the criteria is indicated with '+'/'–', respectively. The analysis is performed for the same 45 papers that were chosen and analysed in Sect. 3 with the same sequence of papers and the division based on "planning type" property. The last row of the table summarises the number of papers that have included each of the criteria.

## 4.3 Analysis

Table 4 shows that the most often used CRA criterion is DCPA, used in 21 (47%) papers, whereas TCPA was used in 15 (33%) papers. 14 (31%) papers use both TCPA and DCPA, whereas half the papers (23, or 51%) use neither TCPA nor DCPA as a CRA criterion. Most of these 23 papers are dealing with static obstacles; therefore, there is no need for calculating CPA. Instead, authors in Tam and Bucknall [54] use a two-step CRA process by (1) determining the type of encounter, and (2) calculating the dimensions of the safety area. The rest of the 23 papers that do consider dynamic encounters use other ways to ensure safety, and collision-free paths, such as considering COLREGs [16, 24, 40, 53], applying a safety domain around own or target vessels [24, 53, 54], or calculating the probability of collision [52].

Regarding the objective function, path length (27 papers, or 60%) is the component taken into account the most, followed by smoothness (13 papers, or 29%), time (12 papers, or 27%), and lastly energy efficiency (8 papers, or 18%). 10 papers use none of the four objective function components, and no paper uses all four. In most of these cases, the papers are dealing with collision avoidance [9, 15, 47, 51, 52, 53, 55]; therefore, authors do not prioritize optimization of the path's length, energy efficiency, or other parameters but instead focus on safety of the collision-free path. Other components included in objective functions by some authors are tractability [31]; cost on deviating from the relative nominal trajectory, and on control input [41]; and navigation restoration time and angle during collision avoidance manoeuvre as well as optimal safe avoidance turning angle [18].

Algorithms based on reinforcement learning (RL) [e.g., 49] do not use a standard objective function but rather a reward function. This means that standard objective parameters are not optimised directly. Instead, the reward function helps the agent to learn and improve based on the dynamics of an agent and the practicality and safety of the path. Therefore, even though RL algorithms do not optimise smoothness directly, they might generate a path that is smooth.

**Table 4** The use of CRA and objective function components in 45 selected papers

| Reference | CRA | | Objective function | | | |
|---|---|---|---|---|---|---|
| | TCPA | DCPA | Length | Time | Smoothness | Energy |
| [25] | – | – | + | – | – | + |
| [26] | – | – | + | – | – | + |
| [12] | – | – | + | – | – | – |
| [27] | – | – | – | – | – | + |
| [28] | – | – | – | – | – | + |
| [29] | – | – | + | - | + | + |
| [30] | – | – | + | – | + | – |
| [31] | – | – | + | + | - | – |
| [32] | – | – | + | + | + | – |
| [33] | – | – | + | – | + | – |
| [19] | – | – | + | – | - | – |
| [34] | – | – | + | – | – | – |
| [35] | – | – | + | + | – | + |
| [36] | – | – | + | – | + | – |
| [22] | – | – | + | – | – | – |
| [20] | – | – | + | – | – | – |
| [17] | – | + | – | – | – | – |
| [14] | – | + | + | – | + | – |
| [37] | + | + | + | – | + | – |
| [38] | + | + | + | – | + | – |
| [39] | – | + | + | + | – | – |
| [16] | – | – | – | – | – | – |
| [24] | – | – | + | – | + | – |
| [40] | – | – | – | + | - | – |
| [21] | + | + | – | + | – | – |
| [41] | + | + | + | – | - | + |
| [42] | + | + | + | + | – | – |
| [43] | + | – | + | + | – | – |
| [44] | – | + | – | – | + | – |
| [45] | + | + | – | + | – | – |
| [46] | – | + | – | – | + | – |
| [47] | + | + | – | – | – | – |
| [48] | – | + | + | – | + | – |
| [49] | + | + | – | – | – | – |
| [50] | – | – | – | – | – | + |
| [15] | + | + | – | – | – | – |
| [5] | + | + | + | + | – | – |
| [51] | + | + | – | – | – | – |
| [52] | – | – | – | – | – | – |
| [53] | – | – | – | – | – | – |
| [54] | – | – | + | + | – | – |
| [9] | + | + | – | – | – | – |
| [55] | – | + | – | – | – | – |
| [18] | + | + | + | + | – | – |
| [23] | + | + | + | – | + | – |
| Total | 15 | 21 | 27 | 12 | 13 | 8 |
| % | 33 | 47 | 60 | 27 | 29 | 18 |

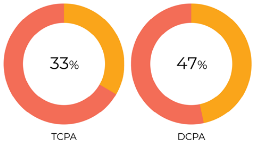


**Fig. 5** Usage of the CRA components TCPA and DCPA in 45 selected papers

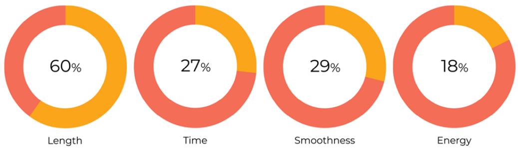


**Fig. 6** Usage of the objective function components Length, Time, Smoothness, and Energy in 45 selected papers

Statistics of CRA and objective function components included in the papers are summarised in Figs. 5 and 6, respectively.

## 5 Advantages and limitations

To further enhance our comparative study of path planning and collision avoidance algorithms for ASVs and USVs, we summarise the advantages and limitations (room for improvement) of the algorithms proposed in the 45 selected papers, as shown in Table 5. The criteria of the analysis include computational complexity, convergence, planned path features (particularly optimality and smoothness), the ability to re-plan, operation in real time, the complexity of the environment, consideration of the local minima trap, and others.

The analysis of the advantages and limitations of the proposed algorithms is based purely on the information provided by the authors of each one of the analysed papers. Therefore, this evaluation is inherently subjective, and in most cases, the authors have not stated the limitations of the algorithms at all even if they exist (noted in the table as 'N/D') or they have been extracted from the future work section.

The analysis of the algorithms in Table 5 shows that in many papers, authors do not state their limitations in a straightforward manner. In many cases, the limitations of the proposed algorithms have been extracted from the future work section of the paper. This section often gives a better comprehension of the current state of the proposed method and its limitations and parts that have to be improved.

In some cases, the conventional version of an algorithm has been extended and improved to form promising derived algorithms that avoid limitations of the conventional algorithm. For example, a well-known limitation of the conventional APF algorithm is the local minima problem. However, for derived algorithms that are based on the conventional APF, authors often state avoiding local minima trap as their advantage, additionally to other improvements.

To sum up, many of the proposed algorithms are trying to overcome different problems connected with developing an autonomous system that performs well in real-life applications. However, the analysis shows that even when the limitations of the algorithms are not stated clearly by the authors, they still exist. That is, although researchers demonstrate knowledge about which components should be included in an ASV path planning and collision avoidance system, there inevitably will still be difficulties in implementing the system in real life.

Finally, we wish to point out that, according to our knowledge, several other path planning algorithms used for mobile robots, ground vehicles, aerial vehicles, or underwater vessels have not been applied to surface vessels yet, e.g., bug algorithm [64], Voronoi fast marching method [65], symbolic wavefront expansion [66], probabilistic roadmaps [67], and fast marching* (FM*) [68]. Even though these algorithms have been applied for path planning in various other fields, it would be possible to adapt these algorithms also to applications for ASVs. Moreover, interested readers should note that additionally to our own comparison of algorithms, and a comparison of performance of the A* algorithm and derivative algorithms (A*PS, Theta*, and A*GB) used for path planning for autonomous inland vessels is provided by Chen et al. [34].

## 6 Discussion

The timeline of algorithms for the latest decade shows an increased interest of researchers for solving path planning and collision avoidance problems for surface vessels by experimenting with, and developing new, methods and algorithms from the AI domain. However, this comparative study shows that there is still no unambiguous model of how "the ultimate" autonomous ship should be designed, which components it should include, and how it should act. The analysed papers offer various solutions to example problems, but these solutions are often limited to perform well under specific and restrictive conditions.

Through the analysis, we have identified a number of limitations in recent solutions for path planning and collision avoidance of ASVs (some of these limitations have also been pointed out in other review papers in the field, as described in our accompanying paper [1]):

**Table 5** Advantages and limitations of the analysed algorithms

| Method | Refs. | Advantages | Limitations |
|---|---|---|---|
| Fuzzy membership function | [55] | The actions of experienced helmsman in ocean navigation are simulated<br>The algorithm avoids close-quarter situations | N/D |
| Fuzzy relational products | [50] | The path to the goal is reasonable, optimal, and safe<br>Compliance with COLREGs<br>System is a practical and effective candidate for a real-time path planning | N/D |
| Modified artificial potential fields | [17] | Local minima avoidance<br>It effectively solves the online path planning problem | The resulting path exhibits some jaggedness<br>It is difficult to tune gains to achieve specific clearances |
| Finite Angle A* | [33] | The vessel's dimensions and its turning ability are considered<br>It keeps safe distance from the path to obstacles<br>Can be used in real time<br>The resulting path is more pragmatic and can be utilized by a USV directly<br>The algorithm can be used on binary satellite images | N/D |
| A* Post-Smoothed + DW | [36] | Reduced number of waypoints by eliminating redundant turns<br>Resulting path is the shortest path<br>The motion dynamics of the USV are considered<br>Remarkable performance and superiority in path planning with obstacle avoidance<br>The USV can avoid unknown obstacles via selecting optimal velocities | N/D |
| Optimal reciprocal collision avoidance | [15] | Autonomous detection of a collision occurs in real time<br>The proposed approach is both valid and efficient<br>It takes into account the reactive avoidance action of the threatening vessel | The environmental conditions are not considered |
| Voronoi-visibility algorithm | [25] | The generated path is feasible and takes the energy consumption into account based on sea current data<br>The USV keeps a safe distance from all islands and coastlines<br>The path is energy-efficient<br>The proposed algorithm integrates the advantages of the Voronoi diagram and Visibility graph | The sea current data are time-invariant<br>The speed of the USV does not change depending on the sea current state |
| Multi-layered fast marching method | [26] | Generates practical trajectories in dynamic environment<br>Keeps a safe distance away from obstacles<br>Saves on the energy cost by following counter-flow areas | Does not take into account wind<br>Does not follow COLREGs |
| Shortcut Dijkstra + modified APF | [22] | The navigation is efficient both in a changeable and unchangeable environment<br>The algorithm avoids falling into local minimum | Little work is done on trajectory tracking |
| AFMS | [31] | Generates feasible and practical waypoints<br>Calculates the optimal path according to the vehicle's constraints | N/D |
| FMS | [16] | The algorithm avoids falling into local minimum trap<br>The path generated is safer than the one of FMM<br>Compliance with COLREGs | N/D |

**Table 5** (continued)

| Method | Refs. | Advantages | Limitations |
|---|---|---|---|
| Adaptive-BFOA | [21] | The algorithm is applicable in real time<br>The path does not get trapped in local optimum<br>The rules of the road can be properly taken into account<br>The algorithm is very robust and reliable, given the diversity of marine traffic environment | It is assumed that target ships do not change their courses and speeds |
| Multi-objective PSO | [48] | Compliance with COLREGs<br>The system demonstrates its robustness | The algorithm need improvements when dealing with conflicting rules, interaction of autonomous and manned vessels, poor or degraded sensor picture, and manoeuvring in restricted waters |
| ACO | [5] | The algorithm outperforms GA with respect to both execution efficiency and execution results<br>The planned path considers both economy and safety, while being the safety critical, shortest collision avoidance route | No real-time decision support |
| GA | [18] | Saves calculation space and time<br>Provides a practical and meaningful application to the navigator<br>Finds a theoretically safety-critical recommendation for the shortest route of collision avoidance from an economic viewpoint | Only circular shape ship domain is considered<br>The algorithm is not customized for parallel processing |
| ACO | [19] | The algorithm converges quickly | N/D |
| Direction priority sequential selection | [24] | Viable and realistic trajectories<br>Compliance with COLREGs<br>Consideration of dynamics of an actual USV<br>Improved trajectories and computational costs over A*<br>A path is smoother and with less jagged segments than A*<br>Avoids both static and dynamic obstacles | COR for obstacle detection might fail in some cases<br>An edge detection system for obstacles would be more appropriate |
| R-RA* | [14] | The system automatically detects and avoids multiple, dynamic, and pop-up obstacles in compliance with COLREGs<br>Safe navigation is ensured without the need for operator intervention and decision making<br>It is a fast, online solution without dependence on AIS data<br>The computational time is saved by doing only local replanning | Vessel dynamics are not considered<br>The current system could be improved by incorporating optimal speed assignment in addition to the recommended spatial path |
| APF-ACO + multi-layer algorithm | [20] | Faster convergence than that of the ACO algorithm<br>The method overcomes the problem of premature convergence<br>It offers a solution in a complex environment | The environmental disturbance during the obstacle avoidance should be reduced<br>Precision should be improved |
| Deterministic algorithm | [51] | The algorithm is algorithmically complete (the outputs from the algorithm are entirely predictable)<br>Practical and COLREGs compliant navigation path<br>The path planning is based on good seamanship practice<br>The algorithm will not return the vessel to its initial course unnecessarily after the avoidance manoeuvre | The avoidance of area-based obstructions has not been implemented<br>The reactive planning subroutine is included only partially<br>The energy management and mission planning modules have not been implemented yet |
| A* on border grids | [34] | The algorithm takes advantage of grid search and visibility check<br>The algorithm reduces unnecessary heading changes, it is faster than traditional A* and proposes shorter path for inland path planning | The impact of infrastructures and real-time information are not included in this paper |

**Table 5** (continued)

| Method | Refs. | Advantages | Limitations |
|---|---|---|---|
| Artificial potential fields | [44] | The algorithm is effective in complex navigational situations<br>Real-time collision avoidance<br>Compliance with COLREGs | Local minima problem<br>Oscillations in narrow passages<br>Weather conditions are not taken into consideration<br>The simulation does not have any optimisation or prediction ability per se<br>Extreme encounter cases are not considered |
| Voronoi diagrams + Fermat's spiral | [37] | Clearance constraints are satisfied with respect to both land and shallow waters<br>The path is produced real time; it is safe, practical, and intuitive<br>Compliance with COLREGs<br>Low computational cost | N/D |
| Hierarchical multi-objective PSO | [38] | The method generates safe and COLREGs compliant paths<br>A collision-free path is always guaranteed<br>It can deal with multiple-vessel encounters simultaneously | Choosing the optimal safety objective function is still an open problem |
| Probabilistic obstacle handling + A* | [52] | The produced evasive paths keep distances to other vessels<br>The path planning is triggered less frequently (unnecessary manoeuvres due to imprecise measurements are avoided)<br>The collision risk of any path is known | Dynamic adaptations of the parameters should be investigated to suit narrow environments, such as rivers, equally well<br>The accuracy of the algorithm can be improved by approximating the integral that is used to calculate the occupancy probabilities |
| Model predictive control | [53] | The method is conceptually and computationally simple<br>It accounts for the dynamics of the ship, its steering and propulsion system, forces due to wind and ocean current, and any number of obstacles<br>The method is effective and can safely manage complex scenarios with multiple dynamic obstacles and uncertainty | N/D |
| NSGA-II | [23] | Existence of elitism<br>Fast convergence<br>Computationally not complex<br>The resulting path is safe, economical, and considers COLREGs | In practice, there will be a complex sea conditions |
| Evolutionary algorithm | [54] | It deals with close-range encounters, using known and predicted data about the traffic and environment<br>The navigation path is optimal, collision free, COLREGs compliant and practical<br>The algorithm outputs are consistent | The algorithm needs more extensive testing before practical implementation to validate its completeness |
| Deep Q-networks | [12] | Deals with unknown environmental disturbances<br>The algorithm is concise, effective, and extendable<br>The analytic control law is not required to manoeuvre the vessel | N/D |
| COLREG-RRT | [40] | Higher navigation success rate and COLREGs compliance compared to MPC-based and APF based methods<br>More efficient in identifying long-term trajectories given a limited amount of forward simulation calls | The algorithm does not deal with disturbances such as waves and ocean currents |

**Table 5** (continued)

| Method | Refs. | Advantages | Limitations |
|---|---|---|---|
| Velocity obstacles | [9] | The rule hysteresis ensures that each COLREGS manoeuvre is obvious to other drivers<br>The algorithm navigates safely in dynamic, cluttered environments<br>COLREGs are encoded in the velocity space in a natural way | N/D |
| Evolutionary algorithm | [39] | The algorithm works in restricted visibility<br>The method is relatively economical<br>It is capable of finding collision avoidance manoeuvres quickly | The paper addresses ship-to-ship encounters only |
| Pseudospectral optimal control | [27] | The method has proven successful in real-world applications<br>The method is not as sensitive to dimensionality compared to Hamilton–Jacobi–Bellman methods<br>The path is feasible and energy-efficient | The method is not integrated with the complete collision avoidance system |
| Deep deterministic policy gradient | [28] | The reward system is highly customisable and can be changed according to the task and the control model<br>The algorithm automatically generates the perfect path under unknown environmental disturbance | N/D |
| Adaptive wolf colony search | [43] | High speed of global convergence<br>Excellent calculation robustness<br>High-solution accuracy<br>The algorithm can be realized easily and is very suitable to solve the optimization problem<br>With slight modifications, the algorithm can be used in multi-ship collision avoidance path planning | N/D |
| Deep Q-learning | [49] | The approach has great possibility for automatic collision avoidance in highly complicated navigational situations<br>The algorithm is able to avoid collisions in severely congested and restricted waters | The algorithm needs to be enhanced more for realistic applications<br>It does not consider the change of speed as an action for collision avoidance |
| Deep reinforcement learning | [45] | The approach has an excellent adaptability to unknown complex environments with various encountered ships | High sample complexity, difficult to use in learning in the real world |
| Improved quantum ACO | [29] | The algorithm can plan a path considering multiple objectives simultaneously<br>The number of iterations required to converge to the minimum was 11.2–24.5% lower than for the quantum ACO and ACO<br>The obtained minimum was 2.1–6.5% lower than for the quantum ACO and ACO<br>The optimized path for the USV was obtained effectively and efficiently | The kinetic and kinematic constraints of the USV should be added to the cost function<br>More practical environmental loads should be applied to calculate their effects on the path energy consumption of the USV |
| COLREGs-constrained APF | [46] | The method is fast, effective, and deterministic for path planning in complex situations with multiple moving target ships and stationary obstacles<br>The method can account for the unpredictable strategies of other ships<br>A smoother path is achieved by considering the dynamics of the OS | Speed reduction behaviours are not considered<br>Ship dynamics could be more accurate<br>The uncertainty of environmental disturbances and area-based obstructions are not considered |

**Table 5** (continued)

| Method | Refs. | Advantages | Limitations |
| --- | --- | --- | --- |
| Genetic algorithm | [35] | The optimized routes have an advantage in towing tension and satisfy motion constraints | There are drawbacks with regard to solution precision |
| A* with OCP + MPC + BC-MPC | [41] | The hybrid algorithm deals with multi-obstacle situations with multiple simultaneously active COLREG rules, and situations where obstacles violate the COLREGs<br>The ship follows an energy-optimized trajectory unless the moving obstacles interfere | The hybrid collision avoidance system has to be validated in full-scale experiments |
| Path-guided hybrid APF | [42] | The algorithm provides fast feedback in a changeable environment<br>The method has the potential to rapidly generate adaptive, collision-free, and COLREGs-constrained trajectories in restricted waters<br>This method has the potential to perform path planning on an electronic chart platform<br>The algorithm avoids local minima problem, oscillations in narrow passages, and "goals non-reachable with obstacles nearby" problem<br>The method can be used in the fields of USVs, AUVs, and robots | The collision avoidance actions taken by ships are limited to course change only<br>The method should be validated in a more real-life experiment |
| Q-learning | [30] | The approach is more effective in self-learning and continuous optimisation, and therefore closer to human manoeuvring<br>A rational path can always be found | Dynamic obstacles in waterways are not considered<br>Ship collision avoidance rules are not considered in the ship agent model reward function during the process of learning |
| Smoothed A* | [32] | The algorithm reduces unnecessary 'jags', has no redundant waypoints, and offers a more continuous route compared to A*<br>The proposed algorithm outperforms the A* algorithm in terms of turning and distance cost<br>The algorithm can be integrated and applied for real applications | The effect of a complete loss of navigational data needs to be investigated<br>The hydrodynamic forces are not considered |
| Dynamic reciprocal velocity obstacles | [47] | The method is proactive in dealing with the uncertainty of the future behaviour of obstacles<br>The ASV behaviour is predictable compared with both velocity obstacles and reciprocal velocity obstacles methods, especially when the obstacles are following COLREGs | The effect of uncertain decision variables and unknown disturbances should be studied more |

- The variety of algorithms used for solving path planning issue is wide, with researchers continuously exploring different options and trying to find better and more general solutions.
- Many developed algorithms that appear to be efficient theoretically have not been tested in a real environment or with real traffic data; hence, it is not possible to evaluate their efficiency in handling real-world issues.
- Some algorithms deal only with static obstacles, excluding dynamic ones.
- In many cases, the developed algorithms do not take into account external disturbances such as wind, waves, or current, which means that the modelled environment is not complete and the performance of the algorithms under realistic conditions would differ.
- Some algorithms assume that the velocity of target ships (that need to be avoided) is constant, and/or that target vessels do not follow COLREGs, meaning that the controlled vessel is not observed and is ignored by other vessels, which is not very realistic.
- Although many researchers agree that safety is the top priority when navigating vessels, not all solutions are considering COLREGs as part of their safe collision avoidance or path planning algorithm.
- Collision risk assessment is typically based only on one or two factors that do not represent the full comprehension of the safety situation of the own vessel in the environment.

Several of these shortcomings lead to the consideration of non-realistic testing environments for vessels, which, in turn, might cause situations where the behaviour of the vessel at sea will differ from the one in simulation tests.

Regarding the limitations of this comparative study, we wish to highlight the following:

- It could be argued that the algorithms in the selected papers should be sorted depending on whether they are solving a path planning (on the global level) or a collision avoidance (on the local, reactive level) problem. The reason for not doing this is the difficulty in distinguishing the algorithms based on this division, as some algorithms are used both for solving path planning and collision avoidance issues.
- Another limitation is that the comparison of the considered properties only gives a partial understanding of the performance of different algorithms in action.
- Finally, it is difficult to extract sufficient details about the properties of the algorithms because of the incomplete or vague descriptions in some of the papers, thus requiring interpretation by the reader.

Future work should try to address these limitations, and examine in more depth some of the properties in Sect. 3 left out in this study, especially "predictability of environment" and planning with uncertainty.

## 7 Conclusions

The extent of this research is large and fills in some gaps in the field by comparing existing path planning and collision avoidance algorithms of ASVs in a manner they have not been compared before.

ASVs clearly have a big potential in future maritime transportation, but their limitations should also be considered and treated with caution. In this study, we extracted a set of defined properties and characteristics that was used for comparison of the proposed algorithms in 45 carefully selected papers. These properties can be used later by other researchers for benchmarking and for comparing their own algorithm to others'. With respect to the analysis of the 45 papers, the main contribution is threefold and consists of: (1) a comparison of the usage of eight important ship- and environment-related properties; (2) an analysis of how safety has been incorporated, and what components constitute the objective function; and (3) an analysis of advantages and limitations of the proposed algorithms. We consider this comparative study a good attempt at comparing the current state-of-the-art and believe that it can serve as the basis for a deeper performance evaluation system of path planning and collision avoidance algorithms for ASVs.

Future research should be dedicated to simulation as well as real-world field tests that evaluate the actual performance of algorithms in various scenarios under different conditions for a more precise comparison of the developed methods. Such testing systems might aid in evaluating the reliability, durability, and the flexibility of the methods, and in designing appropriate algorithms for specific applications and needs. Testing a large number of different scenarios might be performed using Monte Carlo simulation methods.

Another interesting direction of future research is the evaluation of safety and collision risk assessment of the own ship navigating realistic environments. Components that should be considered when evaluating safety and collision risk are obedience to COLREGs, environmental disturbances, static and dynamic obstacles, and safety domain.

Finally, quantitative and objective evaluation of ASV behaviour should be supplemented by qualitative and subjective evaluation by domain experts such as pilots that could observe ASV behaviour in simulated and real environments. This would lead to improved safety evaluation and could help with designing new quantitative performance measures for evaluating safety and risk in ASV operations.

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# C

# Paper A3

# Evaluation of Path Planning Algorithms of Autonomous Surface Vehicles Based on Safety and Collision Risk Assessment

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***Abstract*—Improved safety while navigating on waters and reduction of collision risk is a vital part of the guidance, navigation and control system of an autonomous surface vehicle. Another problem is, how to compare the performance of existing path planning and collision avoidance algorithms in a unified way. To tackle these problems, a novel evaluation simulator platform is proposed in this paper for simulation-based testing of algorithms. The platform is designed for generating different scenarios based on the system's inputs, such as static and dynamic obstacles, environmental disturbances, vessel's dynamic model, and environment, and to evaluate algorithm performance based on path fitness, risk assessment and, in the future, good seamanship practice. Formation of safety maps is used for assessment of each performance measure. Additionally, a root sum square method combines these measures into a total algorithm performance rating. Finally, multi-objective optimisation is applied to evaluate the algorithms based on their performance ratings.**

***Index Terms*—simulation-based testing, path planning, ASV, collision risk assessment, safety, evaluation**

## I. Introduction

There is increasing popularity in autonomous solutions for guidance, navigation and control of marine surface vessels. Efficient energy usage and improved safety on waters are some main driving forces for introducing new and enhanced path planning and collision avoidance algorithms [1]. A comparative study of 45 such algorithms is performed by Vagale et al. [2]. The study reveals that when it comes to evaluating the safety and fitness of the proposed path, often the developed methods perform well in a specifically tuned environment under predefined conditions and there is no unified way of evaluating them yet.

Testing, verification, and simulation of autonomous surface vehicles (ASVs) and the algorithms used for controlling them are a vital step before ASVs can be safely used in a human-unsupervised environment. However, performing tests using real ships on waters are costly, complex, and, mainly dangerous. A solution to this problem is testing and verifying algorithms and their performance under supervision in virtual simulators. Therefore, the focus of this paper is to propose such a simulator platform with an emphasis on safety evaluation.

According to Rødseth [3] there are five main safety-related issues in guidance, navigation and control (GNC) of autonomous surface vehicles (ASVs):

1) Interaction with other ships and adherence to the Collision Regulations (COLREGs).
2) Propulsion system breakdown, which can lead to grounding, stranding, collisions, or blocking fairways.
3) Failure in object detection, which might lead to powered collisions.
4) Harsh weather conditions that make it difficult to manoeuvre the vessel safely.
5) Error in detection and classification of small to medium size objects (e.g., wreckage, persons, lifeboats) that need to be reported to authorities.

Covering all of these issues is a daunting task. Here, we focus on safety evaluation mainly within guidance and navigation when interacting with other vessels. Safety in navigation may include several factors, such as following guidelines, accounting for environmental factors (e.g., harsh weather conditions), static and dynamic obstacles, considering safety domain around own or target vessels, as well as evaluating good seamanship practice.

Specifically, this paper proposes an evaluation simulator platform (ESP) for evaluating path planning and collision avoidance algorithm performance for ASVs, as well as assessing the generated paths from a safety point of view.

The rest of the paper is organised as follows: Section II provides a review of the existing risk and safety metrics, as well as evaluation frameworks. Section III presents the theoretical framework and scenario architecture of the ESP. Section IV proposes an evaluation method of the algorithms in the ESP. Section V contains a discussion, and finally, some concluding remarks are drawn in Section VI.

## II. Related work

There have been several attempts by researchers to introduce different metrics for safety and risk assessment for path planning and collision avoidance algorithms or autonomous navigation systems. In Vagale et al. [2], we identified four main general safety components (safety conventions, environmental disturbances, ship domain, and collision risk assessment (CRA)), where obedience of them leads to improved safety when navigating on waters. Although these four components have been extensively used in previous studies for risk and safety assessment, the complete list of the assessment criteria is much longer. The following section discusses attempts of previous studies to introduce these metrics.

### A. Risk and safety metrics

Based on our previous work [2, 1], we choose to consider two main categories of risk assessment and safety analysis: (i) collision risk assessment, and (ii) COLREGs compliance evaluation. In many cases, the former is closely connected with the ship domain and its parameters.

*a) Collision risk assessment:* Collision risk assessment is a broad concept across the literature that is used for various applications. In this paper, we focus on assessing the collision risk from a guidance and navigation perspective and evaluating safety while the vessel is traversing a planned path.

Based on the risk definition by Kaplan and Garrick [4], the *risk index* (RI) is a product of the probability (P) of an accident and its consequences (C):

$$RI = P \times C \tag{1}$$

However, we agree with Kaplan [5] that the idea of risk is relative and is a much larger concept than simply a number or a vector. Background knowledge is something that should also be considered when assessing risk. A similar idea is claimed by Montewka et al. [6], arguing that risk is a wider concept and a spectrum of scientific approaches to it varies from being a probabilistic risk measure (realist view) to an observer's perception about a current situation (constructivist's view).

A thorough review of the navigational collision risk (NCR) assessment measures throughout the literature is provided by Ozturk and Cicek [7]. The review demonstrates that there are 41 different NCR assessment parameters considered across the literature, where TCPA and DCPA stand out as the most often used ones. In several papers [8, 9, 10], collision risk index (CRI) is modelled as a function of TCPA, DCPA, and some other factors. The approach of using CPA for estimating collision probability using geometric analysis is called *synthetic indicator approach* [11]. It works by assuming that the target ships will maintain their kinematic status.

The authors in Huang and van Gelder [12] also agree that the traditional collision risk index ignores such important aspects as the possibility of conflict resolution and consideration of the encounter's situation as a whole. To overcome these issues, the authors introduce a time-varying collision risk (TCR) measure. Unlike the most existing collision avoidance measures for autonomous vessels found in the literature, the TCR is also considering the difficulty of avoiding the approaching vessels that pose a danger.

Ship safety domain is another collision risk assessment tool that is used by several authors (synergy ship domain in Zhou et al. [13], and ship domain in Feng et al. [14]). A useful tool, in this case, is a collision risk threshold that presents early warnings of possible danger.

The vessel conflict ranking operator (VCRO) developed by Zhang et al. [15] ranks the encounters of each pair of vessels and prioritises these encounters by considering the distance between ships, relative bearing, and the difference between headings of the ships. An improved version of this near-miss risk assessment model — new vessel conflict ranking operator (NVCRO) [16] — additionally considers the safety domains of both vessels, and possible relative striking locations. A similar model is proposed by Nguyen et al. [17] where a vessels collision warning system simulates a collision assessment based on the AIS information. The parameters provided by AIS are then combined to calculate the collision risk index.

*b) COLREGs:* Compliance with COLREG (International Regulations for Preventing Collisions at Sea) Rules [18] is common practice when navigating on waters. However, these rules are open for interpretation, and that makes it not an easy task to incorporate them into an autonomous system nor to assess their compliance.

The research by Tam and Bucknall [19] proposes to determine the type of the COLREGs encounter situations depending on the bearing and position of the target vessel in relation to own vessel. The area around the own vessel is divided into 6 sectors that correspond to different COLREGs encounter situations. The collision risk, in turn, is assessed based on the intrusion of the own ship's safety domain by a target vessel.

Extensive research on safety convention protocol, such as COLREGs, analysis and evaluation is done by Woerner [20], with subsequent improvement [21]. In Woerner et al. [21], the authors propose using the contact angle and closest point of approach (CPA) technique to detect different COLREGs situations. Woerner has also successfully developed a road test to quantify COLREGs protocol compliance and safety for autonomous surface vehicles (ASVs). The work of Woerner [20], Woerner and Benjamin [22] has also been extended by several other researchers, including Stankiewicz and Mullins [23], Minne [24].

### B. Risk assessment frameworks

Different risk assessment frameworks that have been developed for risk and safety evaluation in maritime navigation are dealing with a larger picture than just the collision risk index calculation. Some promising frameworks are reviewed in this section. Although they are a useful attempt to analyse different maritime traffic situations from the safety perspective, the focus on simulation-based testing of path planning and collision avoidance algorithms is a focus of only a few papers.

Goerlandt et al. [25] developed a framework for maritime risk-informed collision alert system (RICAS) using a fuzzy expert system as a risk measurement tool. Zhen et al. [26] proposes a real-time multi-vessel collision risk assessment framework that, firstly, detects clusters of vessel encounters and, secondly, calculates CRI (collision risk index) matrix for each cluster based on the TCPA and DCPA parameters.

A thesis by Minne [24] presents an attempt to automatically test collision avoidance algorithms using the CyberSea simulator. The focus of this framework is on COLREGs evaluation using the safety function proposed by Woerner [20]. Similarly, an ASV performance evaluation methodology by authors Stankiewicz and Mullins [23] assesses a (i) mission score, (ii) safety score, and (iii) COLREGs score (based on [20]).

A slightly different approach for the safety verification of autonomous ships is proposed in Rokseth et al. [27]. In this paper, the authors use a hazard identification model called Systems-Theoretic Process Analysis (STPA) to derive a safety verification program and generate a test-case set already at an early design phase of autonomous ships.

Pedersen et al. [28] propose a simulation-based testing system for autonomous navigation systems using the Open Simulation Platform (OSP). This test system is comprised of a virtual world and a test management system. The test scenario evaluation is done using two methods: (1) evaluation of compliance with COLREGs by Woerner [20], and anxiety estimation by Nakamura and Okada [29]. The architecture of this test system is similar to what we assume the test system in our ESP should be. Nevertheless, here, the main focus is on the "test evaluation" part.

A quite different application of safety index and risk criteria evaluation in maritime navigation is proposed in [30]. The framework presented in the paper analyses the risk level in waterways based on the historic data of accidents.

Although the application and approach of these methods might vary greatly, the evaluation metrics remain similar. Some papers point out that recent studies in multiple ship encounter situations focus on multiple pairwise encounters using micro-level risk models [12, 16]. This allows to reduce the complexity of the analysed space and speed up the risk assessment procedure. However, in multiple vessel encounter situations, this might lead to erroneous interpretation of the actual risk between vessels. We conclude that a yet to be resolved issue in the field is determining collision risk for multiple ship encounter scenarios considering more that one target vessel simultaneously.

Another identified issue in the literature is automatic scenario generation for testing. Here, a stumbling block is the generation of a situation instance that represents a close-to-real life situation. In our opinion, one of the possible solutions for this issue is proper use of historic AIS data. Finally, the evaluation of good seamanship practice is still an open problem. In this paper, we open a discussion about this topic with the aim of gaining a better understanding of it and incorporating it into the proposed ESP in the future.

## III. Evaluation simulator platform

The previous literature review in Vagale et al. [2] comparing the applied path planning and collision avoidance algorithms for ASVs revealed the need for a method to assess and compare different path planning algorithms and their performance. There are several parameters that need to be determined in order to evaluate the performance of path planning algorithms in terms of safety, efficiency, and good seamanship practice. With so many varying parameters, this turns out to be a multi-objective optimisation (MOO) problem. The following subsection proposes the concept of an ESP that can be used for comparing different path planning algorithms and their performance.

### *A. Theoretical framework*

To be able to extensively test and compare different path planning algorithms of ASVs in various situations, it is necessary to generate different scenarios under various conditions. As presented in Fig. 1, the proposed ESP comprises the following input parameters needed for scenario generation and testing: map, static obstacles, dynamic obstacles and their movement, environmental conditions (such as wind, waves, current), vessel's dynamical model, algorithms that are going to be tested, and the safety evaluation function.

Using the aforementioned input parameters, scenarios are being generated in the ESP. In each scenario, when the simulation starts running, the own vessel (with varying vessel's dynamic model) finds a safe path from the start pose to the end pose using different path planning/collision avoidance algorithms. While doing that, the vessel should take into consideration the known static obstacles, avoid dynamic obstacles, such as target vessels, and consider environmental disturbances. As the result of applying a safety evaluation function for each scenario, the ESP outputs are the algorithm performance results, based on: (i) path fitness evaluation, (ii) safety and risk assessment of the generated path, and (iii) good seamanship practice evaluation. All three components are explained in detail in Section IV.

To make the testing scenarios correspond to real-life situations, the performance of algorithms should be compared both in predicted and unpredicted environments that are not known in advance. Therefore, we also include unpredicted objects as part of a scenario, and these objects are "visible" to own vessel only from a certain distance. In this situation, the environment is not fully known, so the algorithm might deal with some unpredicted objects/obstacles that are in its way. This type of testing evaluates the algorithm performance in near-real life situations.

### *B. Scenario architecture*

The previous subsection explained the general inputs and outputs of the proposed ESP. Here, we explain in detail the generation of the scenario, its components, the acquisition of different safety maps, and their merger.

Different input parameters of the ESP (as seen in Fig. 1) lead to the generation of different scenarios and testing of the path planning and collision avoidance algorithms based on the specified safety evaluation function. Figure 2 illustrates the general idea of how each scenario is generated.

For the safety evaluation purpose, a multi-layer safety map is formed consisting of the following layers: (i) static safety map, (ii) dynamic safety map, and (iii) other types of safety maps.

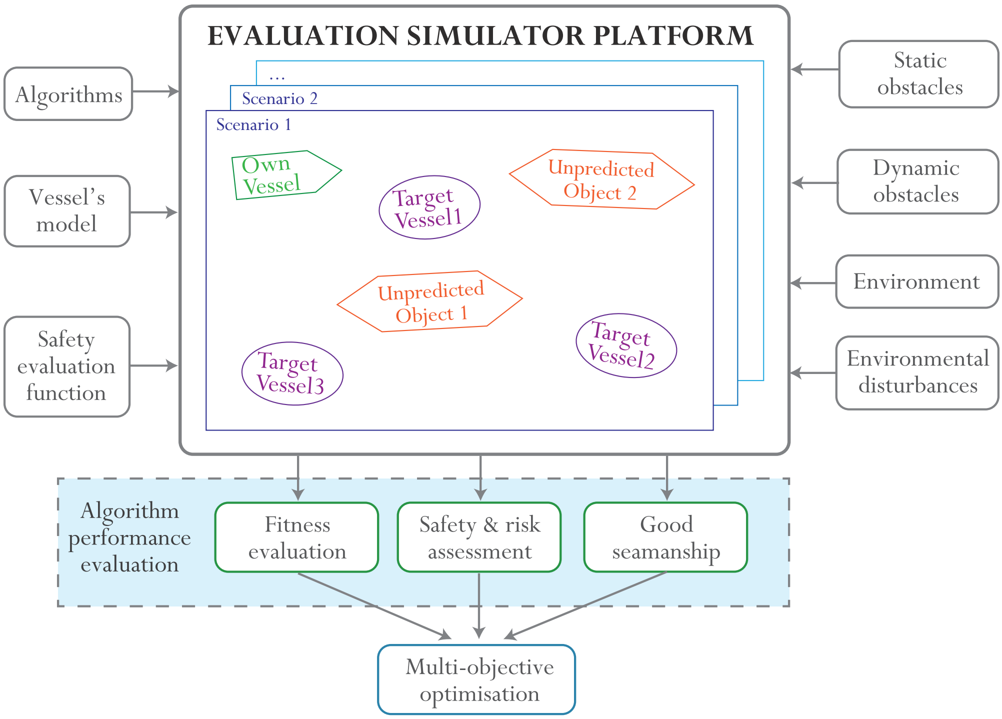


Fig. 1. The concept of the algorithm evaluation simulator platform

*1) Static safety map (SSM):* For the static safety map formation, it is necessary to import a nautical chart, e.g., an electronic navigational chart (ENC), of the area where the own vessel is planning to navigate. Nautical charts nowadays available for mariners provide useful information about depths of water, as well as topographic maps of the land, coastline details, harbours, bridges, buoys, lighthouses, etc. All these data are time-independent.

The static safety map is a 3D graph with geographic coordinates on axes x and y, and safety values 0 to 1 on the axis z. This safety map represents the risk level of own vessel if situated at any coordinates, and it is based on the information from the previously mentioned nautical chart.

First, it is assumed that all the land coordinates have a risk value of $R(x, y) = 1$ (high risk). This means that it is highly undesirable for a vessel to drive on land (to strand). Similarly, the coordinates of the rest of the map, such as open waters or waterways with safe passage are assumed to have a risk value of $R(x, y) = 0$ (low risk). Afterwards, a transient safety distribution function (e.g., s-shaped membership function) is applied to the map to obtain a smoothly distributed static safety map. Similarly, depending on the own vessel model, some areas of the shallow water might have elevated risk values due to the danger of grounding. It is important to remember that the SSM, even if looking similar, is not a topographic profile of the area.

*2) Dynamic safety map (DSM):* In the proposed ESP, we consider two possible ways for modelling movement and paths of dynamic obstacles (target vessels). The first is to extract the information about real vessels' routes from the historic automatic identification system (AIS) data of specific vessels over a defined time. In this situation, the movements of target vessels are more realistic, however, unless modified, they would treat the own vessel as a "ghost vessel" and would not apply the corresponding COLREG Rules to avoid it. The second option is to generate target vessels' paths using one of the several path planning and collision avoidance algorithms analysed in Vagale et al. [2]. The paths generated this way might construct less realistic simulation, however, that would lead to mutual collision avoidance when own vessel meets target vessels.

The principle of generating a dynamic safety map is similar to the previous one. However, in this situation, the risk values are based on the safety domain around vessels and probabilistic obstacle handling of target vessels [31]. Another important difference is that the movement of vessels is dynamic, therefore, this safety map is time-variant.

*3) Other safety maps:* Under this category fall maps that represent additional information that might be useful for the

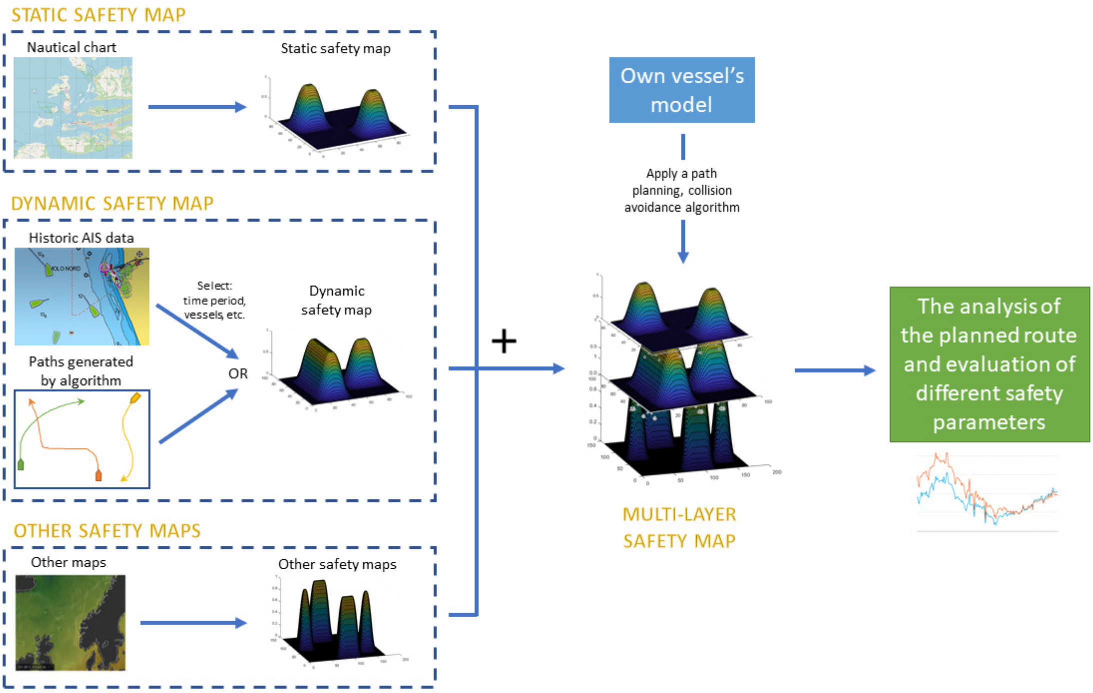


Fig. 2. The generation of each scenario

vessels navigating in the area. In the simplest case, other maps might include information regarding the environmental conditions, such as wind, air pressure, temperature, precipitation, wave height, current. For other types of maps, the way of acquiring the corresponding safety map depends on the type of data they contain and it is not unified.

*4) Multi-layer safety map:* After the acquisition of each type of safety map described above, the total multi-layer safety map is calculated by adding all the single safety maps together, possibly with weighting. The weighting could be a simple scale factor for all coordinates of a map, or follow some distribution, for example, related to the current position of own vessel (where near-distance coordinates get a higher weighting). Figure 3 represents an example of the total multi-layer safety map with a red vessel's route on it.

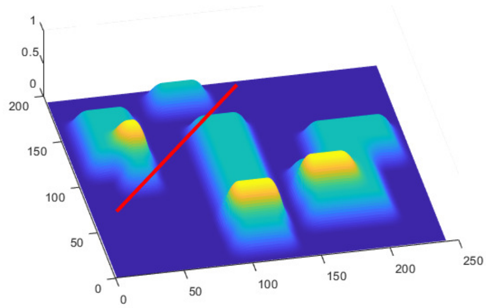


Fig. 3. The multi-layer safety map example with a path (red line) on it.

## IV. Evaluation of algorithms

The performance of path planning algorithms depends on several aspects. In this paper, we distinguish three approaches to evaluate the performance of algorithms: (i) fitness of the developed path, (ii) safety evaluation and risk assessment when traversing the path, and (iii) good seamanship practice. However, having these three evaluations do not immediately answer the question about which algorithm provides the safest, most efficient, and closest to a real-life path. In an attempt to do that, we propose to combine the evaluations in a multi-objective optimisation (MOO) problem.

The main focus of the proposed evaluation method is on the safety aspect from a path planning point of view. That might include a variety of different approaches, such as compliance with COLREGs, consideration of both dynamic and static obstacles in time, environmental disturbances, intrusion of the safety domain of the ASV, and collision risk assessment metrics.

### A. Fitness

The research performed by authors in Vagale et al. [2] demonstrates that the most often used objective function criteria to evaluate the fitness of the planned path is path length followed by smoothness and voyage time. Based on these results, we begin with considering only two criteria for the assessment of path fitness $F(p)$, namely (i) path length and (ii) voyage time. Path length $l(p)$ is the sum of the length of each path segment, whereas voyage time $t(p)$ represents how much time does it take to traverse this path considering environmental disturbances, dynamics of the vessel and other factors. Constants $w_l$ and $w_t$ are introduced as weights for the length and time variables correspondingly. Both of these variables are combined in a fitness function:

$$F(p) = l(p) \cdot w_l + t(p) \cdot w_t \quad (2)$$

Reducing energy consumption is also an important objective in autonomous vessel navigation. However, due to the simplified vessel model, this objective is not included in the fitness calculation. In later stages, the fitness assessment can be extended with algorithm efficiency measures, such as computational time, and computational resources.

### B. Safety assessment

The multi-layer safety map, acquired by the merger of single safety maps (described in Section III), is used as the basis for the safety evaluation of the vessel's path. The risk assessment in the ESP is based on the geometric point of view.

Firstly, the vessel's path is divided into waypoints at constant time intervals. Secondly, a risk value from the obtained multi-layer safety map is extracted for each waypoint's coordinates. This results in an array of risk values, where the length of an array equals the number of waypoints in the path. Subsequently, we propose to use the root sum square (RSS) method to calculate the total risk $R$ of the traversed path:

$$R_{RSS}(p) = \sqrt{({s_1}^2 + {s_2}^2 + \cdots + {s_n}^2)} = \sqrt{\sum_{i=1}^{n} {s_i}^2} \quad (3)$$

In Eq. 3, $R_{RSS}(p)$ is the root sum square risk value of the path, $p$ is a generated path of the own vessel, and $n$ is a number of waypoints in the path.

We consider the RSS method appropriate for this application because it emphasises high-risk values more than the traditional sum or mean value. The total risk value can be used for comparing paths generated by different path planning algorithms, and for indicating which path would be safer to take for the vessel to avoid collision risks or grounding/stranding danger. This is a simple and relative way of evaluating the safety of the path, and in future research, we intend to conduct several tests of the method and improve the existing function.

Another informative tool for risk assessment at each waypoint coordinate is a polar obstacle density (POD) method, proposed in Lee et al. [32], where this method is used for finding the optimised collision avoidance scenario. However, in the ESP, the authors are planning to use it as an informative tool for a more detailed assessment of risk at each waypoint. Compliance with COLREGs is another aspect that should be included in the safety evaluation in maritime navigation. As already mentioned previously, an exceptional job in this field so far is done by Woerner [20], and, in the future, it might serve as a basis for evaluating COLREGs compliance in the ESP.

### C. Good seamanship practice

Good seamanship practice is a common practice of how to deal with situations that are not explained by rules. Even if the definition would be clear, it is nearly impossible to cover all the possible and unpredicted situations. Following COLREGs is considered as good seamanship, however, due to the vagueness of the rules, it is complicated to implement several of the rules in an autonomous system. An attempt at incorporating mariner's judgement in a risk model is provided in Lopez-Santander and Lawry [33], where authors admit that it is a powerful yet complex tool that needs further investigation.

Another problem is that good seamanship requires more knowledge than just the states and positions of the own and target vessels, and the followed path in the environment. In order to assess the good seamanship practice, it is necessary to look wider — gain better situational awareness (visibility level in the environment, image analysis to determine whether ships standing still are, or are not, at anchor), information from the internal sensors of the surface vessel (the state of the machinery), the correct usage of light signals, and knowledge about whether the target vessel is "under command".

Good seamanship should also consider when not to follow COLREGs, how to hierarchize multiple objectives synergetically [34], navigation in shallow water, and the possibility of equipment malfunctioning and its consequences.

According to Zhou et al. [34], good seamanship required by COLREGs should focus on three aspects: (i) good seamanship, (ii) proper look-out and (iii) vessel not under command. Although a vital part of safety in navigation, at this stage we leave good seamanship practice evaluation as an open question for future research.

### D. Multi-objective optimisation problem

With different types of measures that focus on different aspects of the algorithm's performance and the safety of the path, the total rating of the algorithm is not an easy task. It is constantly a trade-off between different optimisation objectives. As mentioned previously, one way of combining the three previously described parameters and finding one of multiple best solutions is using MOO:

$$min(F(p), S(p), G(p)) \quad (4)$$

where $F(p)$ is a fitness function of the path, $S(p)$ is a safety evaluation function, and $G(p)$ is good seamanship practice evaluation.

A possible solution here is finding Pareto optimality by visualising a Pareto front. Although there is no guarantee that this will typically provide a sole solution by choosing "best" algorithm, the Pareto front represents a finite set of possible solutions around which there is no way of improving any objective without degrading at least one other objective. The choice of trade-offs depends on the situation, and objectives.

## V. Discussion

We have several ideas for going forward with this research. The first relates to the introduction of realistic situations in testing, where we are considering using maritime training simulators for validating path planning and collision avoidance algorithms. In such a situation, a virtual autonomous vessel would be incorporated in the training simulator. In this way, the own virtual vessel would interact with the young cadets who are practising driving the vessel and hence experience a more realistic scenario on waters.

Another topic for consideration is automatic scenario generation. In our view, to obtain a realistic scenario, it is important to access data of real traffic scenarios. A vast source of such data is stored as historic AIS data. This then becomes a question of interpretation of these data and putting them to use correctly. In the case of lack of data, a possible solution would be to use artificial intelligence methods for new scenario generation based on existing data.

## VI. Conclusions

Aiming at the problem of there being no unified way of evaluating path planning and collision avoidance algorithms for ASVs, a novel evaluation simulator platform is introduced in this paper. In this context, a safety evaluation method is proposed using root sum square risk values based on static, dynamic, or other types of generated safety maps. The total algorithm performance assessment is based on the path fitness, safety evaluation method, and in the future also on good seamanship practice. For combining these multiple objectives, the authors propose to view it as a multi-objective optimisation problem. The proposed ESP is currently in the development phase.

In the final stage and with few adjustments, the ESP could aid in evaluating and benchmarking newly developed path planning algorithms not only for ASVs, but also for autonomous underwater, ground, and aerial vehicles.

Future research should consider the development of a credible evaluation method for good seamanship practice. Such a method would be a vital part of the proposed ESP and would provide beneficial research in this field. Future investigations are also necessary to validate the proposed safety evaluation method.

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# D

# Paper A4

Article

# Simulation and Estimation of Extended Collision Risk for Autonomous Surface Vehicles Based on a Fuzzy Inference System

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**Abstract:** Autonomous surface vehicles need to be at least as safe as conventional vessels, if not safer when navigating on waters. With a great deal of navigation algorithms for surface vessels out there, the safety of their produced paths is questionable, and, in most cases, complicated to assess and compare. Hence, this paper proposes a method for extended collision risk assessment for paths generated by autonomous navigation algorithms as follows: 1) static, dynamic, and historic individual risk factors are calculated; 2) individual collision risk value is determined using a fuzzy inference system; 3) the total collision risk is acquired using a root-mean-square method. Finally, a comparison of the total risk values of each path determines the path with the lowest risk. Here, the historic risk factor is based on the detected near-miss collision points from the automatic identification system data. Additionally, the rule base of the fuzzy system is developed based by consulting with a group of nautical experts. The validation results show that the proposed method is able to detect lower / higher risk scenarios and assign an adequate risk value. This research also reveals several promising future directions and applications of the method for navigation algorithm evaluation.

**Keywords:** autonomous surface vechicles; collision risk; safety evaluation; simulation-based testing; fuzzy inference system; expert rule base

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## 1. Introduction

In the shipping sector, a great emphasis is recently set on the green shift. Two main focus areas for driving this change are energy-efficient shipping and alternative energy (fuels). While the latter one is a whole different field, the former one can be improved by optimising various factors in both ships' electronics and mechanics (hardware part), and by efficient path planning (software part). Introducing autonomy in shipping goes well along with efficient path planning and optimisation of the navigation. Furthermore, the importance of safety and risk assessment in shipping has been confirmed by the Norwegian Maritime Authority, who has set safety culture and risk understanding as their main focus in 2022 [1]:

> "*We often see that either a risk assessment of the operations on board is missing, or the risk assessments that have been done are inadequate.*"

While a number of navigation algorithms for autonomous surface vehicles (ASVs) and unmanned surface vehicles (USVs) exists, each one of them has its own advantages and drawbacks. A previous study by the author [2] endeavoured to compare several path planning and collision avoidance algorithms of ASVs. The review lead to a conclusion that there is a vast number of developed algorithms out there and, currently, no unified way of comparing them. To tackle this issue, an evaluation simulator platform (ESP) for comparing the paths generated by the path planning and collision avoidance algorithms for autonomous surface vehicles has been proposed by the authors in Vagale *et al.* [3]. The ESP suggests evaluating paths based on three aspects: (i) safety, (ii) efficiency, and

(iii) good seamanship practice. In this article, the author assumes that the evaluation of paths generated by these algorithms in different scenarios presents an opportunity to compare and improve the understanding of these navigation algorithms. The benefit of using simulation-based testing is that it provides a way to test a vast number of different navigation scenarios under varying and realistic conditions in a safe and cost / time efficient manner.

When evaluating the safety of the vessel traversing a pre-planned path on the water, collision risk assessment (CRA) plays an important role. Although, several methods to evaluate collision risk for ASVs and USVs exist, most of them are incorporated as a part of a collision avoidance or path planning algorithm that seeks a safe path or trajectory. Up to date, the author has not found an existing tool that evaluates and compares paths generated by different navigation algorithms from the safety perspective using these CRA methods.

The focus of this article is on establishment, implementation and validation of the safety assessment component of the ESP. Several various risk and safety components are combined into the extended collision risk estimation method. A fuzzy inference system (FIS) based on an expert rule base is used for combining (i) static, (ii) dynamic and (iii) historic risk factors into the individual risk value for each timestep along the vessel's path. Afterwards, a root-mean-square function calculates the total risk value for the whole path. The obtained total risk values for different paths allows comparing performance of different navigation algorithms. The fuzzy system benefits from incorporating nautical expert domain knowledge linguistically for an improved and more complete view on the risk assessment issue. Here, static risk factor estimates the danger level in terms of grounding / stranding of the vessel. Dynamic risk factor is the result of the collision risk index (CRI) calculation. Finally, historic risk factor is derived from the near-miss collision detection from the historic automatic identification system (AIS) data. Some possible applications for this type of evaluation are for:

- verification / benchmarking of existing path planning algorithms,
- automatic evaluation of paths (instead of manual evaluation),
- algorithm development with improved safety considerations.

### *1.1. Contributions*

This article focuses on implementing the "safety and risk assessment" component of the ESP when comparing paths from autonomous navigation algorithms, as presented in the previous paper by the author [3]. In this paper, CRI is used in combination with other risk assessment methods to evaluate paths generated by different autonomous navigation algorithms in order to determine the safest and the most efficient path in different scenarios. The novelty of this research is:

1. *Application* — the use of risk measures in a simulator for evaluating different path planning or collision avoidance algorithms for autonomous vessels.
2. *Total risk calculation method* — the method of combining different risk measures, to obtain a total risk assessment of the path.
3. *Incorporating expert knowledge* — the rule base of the fuzzy inference system is based on the knowledge of a group of nautical experts.

A risk assessment method proposed in this article in future could be implemented in the maritime training simulators for autonomous navigation algorithm testing as proposed in Vagale *et al.* [4].

### *1.2. Organization*

The remainder of this article is organized as follows: Section 2 lays out previous research in the field. Section 3 proposes the method for individual risk factor and total collision risk calculation, near-miss collision estimation from the historic AIS data, and the use of fuzzy inference system for combining the risk factors. Section 4 describes the practical implementation details, simulation setup, and lays out the results of the validation. Finally, Section 5 presents a discussion, whilst some concluding remarks are drawn in Section 6.

## 2. Background

An ever-increasing body of literature shows that developing a trustworthy collision risk assessment method is a vital part of advancement in the autonomous shipping technology field. Previous literature reviews by Ozturk and Cicek [5] and Čorić *et al.* [6] provide a fine overview of the latest developments in the ship collision risk assessment methods. Both quantitative and qualitative methods are used for collision risk assessment. Some studies applying quantitative methods for risk assessment are [7–9]. Furthermore, Goerlandt and Montewka [10] address the fact that most of the risk assessment approaches are strongly tied to probabilities, although alternative methods also exist. Qualitative methods, including expert knowledge, although possibly more subjective, provide a different view on the risk assessment.

Several studies have combined various risk and safety components to obtain a more complete view on navigation system performance evaluation. The approach proposed in the current article follows a similar idea. One such approach by Stankiewicz and Mullins [11] evaluates the overall performance of the autonomous ship by combining different sub-scores, assessing mission accomplishment, safety and International Regulations for Preventing Collisions at Sea (COLREGs) compliance. These sub-scores are combined into the final score using a weighted sum method. Similarly, Gug *et al.* [12] propose a quantitative collision risk analysis that is based on several factors, such as ship-ship collision risk, ship-structure collision risk and grounding risk (from bathymetry data). Finally, Yu *et al.* [8] are using a rule-based Bayesian reasoning to assess the geometrical collision risk between the offshore installations and passing ships. The risk factors assessed and combined within this method are (i) navigational conditions (ship speed, passing distance, relative bearing, ship type) and (ii) natural environment (sea state, wind, visibility, and day / night time).

Although the range of various methods in this field is vast, the following sections review in detail the collision risk index measure and relative ship motion parameters it might include, fuzzy methods for risk assessment and historic near-miss collision detection.

### *2.1. Collision Risk Index*

According to Zhou *et al.* [13], "CRI is a commonly used parameter in the research on collision avoidance and decision support of ships, which can reflect the degree of collision risk quantitatively." In this article, the author considers CRI to be a degree of collision risk for a ship-ship pair that is based on relative motion parameters between these ships.

The recent state-of-the-art of existing CRI calculation methods is outlined in detail in Huang *et al.* [14]. Two commonly used types of quantitative CRI are the *ship domain* and *closest point of approach* (CPA) methods [15]. In contrast, Gang *et al.* [16] mention three main types of CRI methods: (i) based on CPA, (ii) fuzzy evaluation, (iii) artificial neural networks, additionally to other new methods. This shows that there is no unity in which relative motion parameters should be included in the CRI calculation and how to combine them together.

The CRI concept was first proposed by Kearon [17], where it is calculated purely based on the two CPA parameters. CRI has been a vital part of the collision risk assessment since then. The literature review reveals that even the latest methods are partially based on the CPA parameters [18,19]. However, "such approaches only provide one-dimensional information on the traffic situation" [20]. For this reason, in most cases, they have been complemented and combined with additional motion parameters. The hybrid methods combining both CPA and ship domain are given in Zhou *et al.* [13], Ha *et al.* [15], Lisowski [21], Namgung and Kim [22]. Other less frequently used parameters include distance between vessels, ratio of speeds, relative bearing, ship length, visibility sea state, encounter type, heading [5,14], security vector [23], and others.

### 2.2. Fuzzy methods for risk assessment

In the field of marine navigation, incorporating experts' knowledge in the ship decision support systems (DSS) and collision risk assessment systems is of high importance in developing a reliable system. Using fuzzy inference system for CRA provides a solution for this issue.

A fuzzy approach defining individual ship risk index is proposed in Balmat *et al.* [24]. Using this approach, researchers have been able to combine static (ships' characteristics) and dynamic risk factors (the weather conditions). On the other hand, later literature shows that researchers have been focusing on including the closest point of approach method, both in terms of distance and time, as a fuzzy system input to assess the collision risk. One of such research is provided by Ren *et al.* [25] that utilised time to CPA (TCPA) and distance to CPA (DCPA) parameters in combination with encounter angle for the dynamic risk assessment. Similarly, Ahn *et al.* [26] also combine TCPA and DCPA parameters using a FIS to model the degree of collision risk. In this approach, membership functions are first defined based on simulation results and are later tuned using the neural network ANFIS (adaptive network-based FIS) approach. Likewise, Bukhari *et al.* [27] propose using FIS in a vehicle traffic service (VTC) centre to assess the degree of collision risk in the real-time among multiple vessels in the vicinity. The proposed method fuses such navigational parameters as TCPA, DCPA, ship's bearing and variance of compass degree (VCD) calculated from the conventional VTS equipment. Finally, an extensive risk informed ship collision alert system has been introduced by Goerlandt *et al.* [28]. In the approach, a zero-order Sugeno-type fuzzy inference system combines not only the typical CPA values but also numerous other navigation parameters, such as bow cross range (BCR), speed difference, distance between vessels, relative bearing and heading.

### 2.3. Near-miss collision detection

*Near-miss collision* (NMC) also called *near-collision*, is a type of unplanned vessel interaction that has a potential to lead to a collision between vessels. In reality, it means that vessels passed each other at a close distance, however, no collision occurs [22]. Detection of these high density NMC zones in waters based on the historic traffic data (AIS) could give more information of potentially dangerous / more risky areas that ships should avoid, mainly, because these situations are rarely or never documented.

The most commonly used type of NMC detection examines if the ships' safety domains overlap each other [29]. In such cases, the shape of the ship domain can vary from quite simple to more complex structures among different methods. For example, authors in Namgung and Kim [22] use elliptical shape ship domain with two different radii based on the vessel's length and the ship's velocity. Another work, by Mestl *et al.* [30], emphasises the interest in the rate-of-turn (ROT) of the vessel in the AIS data and suggests combining it with speed over ground (SOG) to find occurrences of non-normal manoeuvres. Research by Grossmann [31], in turn, combines above-mentioned ship domain and rate-of-turn in a new approach to detect NMC. In a different approach, Zhang *et al.* [32] propose introducing vessel conflict ranking operator (VCRO) that includes distance between ships, relative speed and difference between the headings of the two ships. It is important to note that the main motivator of this research is the enormous volume of AIS data and an attempt to reduce the number of possible near-miss collision cases needing further investigation by experts. A review of other quantitative ship collision frequency estimation method is given in [6].

The following section proposes a method for assessing the extended collision risk on the autonomous ships' path that includes calculating (i) ship-static structures collision risk, (ii) ship-ship collision risk (including CRI), and (iii) risk connected with higher risk (based on near-miss collisions) traffic areas from the historic AIS data.

## 3. Extended Collision Risk Estimation

The concept of an evaluation simulator platform (ESP) (see Fig. 1) for simulation-based testing of autonomous navigation algorithms has been proposed previously by Vagale *et al.* [3].

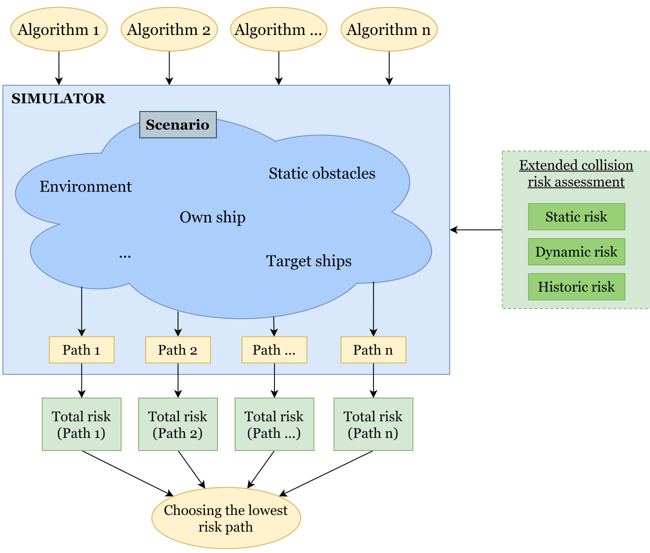


**Figure 1.** Structure of the ESP.

The proposed algorithm performance evaluation comprises three main factors: (i) fitness, (ii) safety and risk assessment, and (iii) good seamanship practice. Fitness, in this context, considers the efficiency of the path that the algorithm has generated. Efficiency can be viewed at from different perspectives, such as path length, travel time, fuel consumption, costs. As for the safety and risk assessment, here, the author looks at extended risk of collision at each point of the traversed path. Good seamanship, in turn, should consider evaluation of whether navigating the generated path would correspond to behaviour on waters expected from an average officer.

The focus of this article is narrowed down to implementing solely the second measure, to evaluate safety and assess extended collision risk of the planned path. The implementation of the first and third factors and combining them is left for future work.

The total collision risk ($\mathcal{R}_{total}$) evaluation method (see Eq. 1) includes three components:

- static risk,
- dynamic risk, and
- historic risk.

$$\mathcal{R}_{total} = f(r_{static}, r_{dynamic}, r_{historic}) \tag{1}$$

It is anticipated that more dangerous (incautious) paths (closer to the land / static structures / target ships, and last-minute collision avoidance) will have higher total risk value. In later stages, it could also be possible adding other components, such as the environmental risk factor that represents risk based on the real-time or historic weather data, COLREGs compliance evaluation scores as proposed in Hagen *et al.* [33].

### *3.1. Static risk factor*

In this article, the static risk factor (SRF) represents the risk of a vessel stranding or grounding in regard to other static objects / structures in its vicinity. These objects may include a landmass, islands, bridges, lighthouses, and other offshore structures in the water. Usually, data about these objects is available in the electronic navigational charts (ENC) and they could be detected using the situational awareness sensors installed on the surface vessel.

The static risk measure calculated in the simulator is based on the relative distance ($d_{SO}$) from the own ship (OS) to the closest static obstacle, in this case, a landmass. This parameter is extracted from the simulator at every timestep along the vessel's path. In order to emphasise the higher risk areas that are close to static obstacles, an exponential function is applied to this parameter to acquire a more comprehensive static risk measure. However, landmasses that are too far from the own ship are of no interest. Therefore, the area of lookout is introduced around the own vessel. For a visual representation of the above-mentioned static measures in relation to the own vessel, see Fig. 2. This defines the area in which a non-zero static risk is calculated. The radius of the area of lookout ($\mathcal{D}_s$) depends on the length of the vessel ($l$). Static risk within this area is calculated using the following equation:

$$r_{static} = \begin{cases} e^{-\frac{d_{SO}}{\tau}}, & \text{if } d_{SO} \leq \mathcal{D}_s \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

Here, the time constant value is: $\tau = \frac{\mathcal{D}_s}{4}$. Values of the static risk outside this area equal to zero. The own vessel with the area of lookout around it and the relative distance to the nearest static obstacle are represented in Fig. 2.

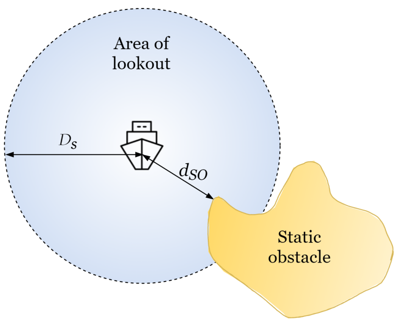


**Figure 2.** Representation of the area of lookout around the surface vessel and a static obstacle in the close vicinity.

### *3.2. Dynamic risk factor*

The dynamic risk factor (DRF), in this paper, is considered a geometrical collision risk associated with interactions between the own vessel and other dynamic obstacles, such as target ships in the vicinity. In autonomous navigation systems, collision risk index is often used as the sole collision risk evaluation measure. However, in this paper, CRI is considered as the dynamic risk factor, that is a component of a larger total risk value:

$$r_{dynamic} = \begin{cases} CRI, & \text{if } d \leq thres \\ 0, & \text{otherwise.} \end{cases} \tag{3}$$

To ensure that only the target vessels in the close vicinity are considered potentially risky, an area of lookout is introduced here as a threshold (*thres*) value.

As covered in Section 2, several CRI evaluation methods exist. The author has implemented three of such CRI methods based on the closest point of approach, by Kearon [17], Lisowski [21] and Mou *et al.* [19]. In order to calculate the CRI values, several geometric relation and motion parameters of a ship-ship pair interaction have to be extracted (see Fig. 3).

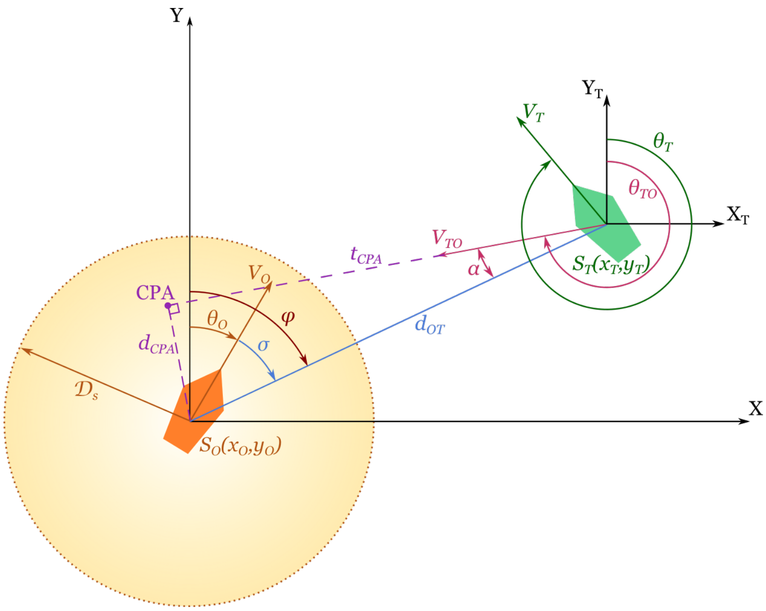


**Figure 3.** Geometric relation and motion parameters of two interacting ships – own ship (orange) and target ship (green). Idea based on Chen *et al.* [34].

These parameters, calculated at every timestep for a ship-ship pair, are:

- $d_{OT}$, relative distance between the two encountered ships,
- $\sigma$, relative bearing,
- $d_{CPA}$, distance to the closest point of approach, and
- $t_{CPA}$, time to the closest point of approach.

Distance and time to the closest point of approach (DCPA and TCPA, respectively) are two parameters that are often used as part of the CRI calculation, and are necessary for the calculation of the CRI values in this paper. $d_{CPA}$ and $t_{CPA}$ components are calculated using the following equations:

$$d_{CPA} = d_{OT} \times sin(\theta_{TO} - \varphi - \pi) \tag{4}$$

$$t_{CPA} = \frac{d_{OT} \times cos(\theta_{TO} - \varphi - \pi)}{V_{TO}} \tag{5}$$

$$d_{OT} = \sqrt{(x_T - x_O)^2 + (y_T - y_O)^2}. \tag{6}$$

where $(x_T, y_T)$ are target ship coordinates, $(x_O, y_O)$ are own ship coordinates, $\theta_{TO}$ denotes relative heading, and $\varphi$ denotes azimuth of the target vessel. Additionally, a spatial ($\mathcal{D}_s$) and temporal ($\mathcal{T}_s$) safety domains for dynamic interactions are introduced around the own vessel and are used for the CRI calculation. To sum up, the dynamic risk calculation includes the following components — $d_{OT}, \sigma, d_{CPA}, t_{CPA}, \mathcal{D}_s, \mathcal{T}_s$.

When these parameters are acquired, it is possible to calculate the CRI measures. First, Kearon [17] CRI evaluation model is using a polynomial equation to combine the $d_{CPA}$ and $t_{CPA}$ measures:

$$CRI_1 = (a \cdot d_{CPA})^2 + (b \cdot t_{CPA})^2. \quad (7)$$

The resulting value is a non-normalised risk, so before using this CRI value in the FIS, it has to be normalised. In this equation, $a$ and $b$ are weights that are adjusted based on the relative bearing values as shown in Table 1. The determining factor in this case is whether the TS is approaching from the starboard or the port side.

**Table 1.** Weights $a$ and $b$ depending on the relative bearing, as in Kearon [17]

| Side | Relative bearing ($\sigma$) | $a$ | $b$ |
|---|---|---|---|
| Starboard | $-112.5° \leqslant \sigma \leqslant 0°$ | 5 | 1 |
| Port | $0° < \sigma \leqslant 112.5°$ | 5 | 0.5 |
| Stern | otherwise | 0 | 0 |

The second model used is proposed by Lisowski [21] as shown in Eq. 8. This method calculates a square root of a weighted sum of several interaction parameters, including distance and time to the CPA, and relative distance between two ships:

$$CRI_2 = \sqrt{w_1 \left(\frac{d_{CPA}}{\mathcal{D}_s}\right)^2 + w_2 \left(\frac{t_{CPA}}{\mathcal{T}_s}\right)^2 + w_3 \left(\frac{d_{OT}}{\mathcal{D}_s}\right)^2}. \quad (8)$$

In this equation, weights $w_1$, $w_2$ and $w_3$ are coefficients dependent on the state of visibility, ship length and a type of water area [21]. Before using this CRI value in the FIS, it has to be normalised.

The third CRI calculation method is based on Mou *et al.* [19] that expresses collision risk using an exponential function:

$$CRI_3 = exp^{-|t_{CPA}|/10} \cdot exp^{-|d_{CPA}|} \cdot F_{angle}, \quad (9)$$

here, $F_{angle}$ is a coefficient that represents the relative heading angle between the two encountered ships. For head-on scenarios $F_{angle} = 1$, for the crossing situation, it is 8.5 and for overtaking 2.34 [15]. Before using this CRI value in the FIS, it has to be normalised.

### *3.3. Historic risk factor*

Historic risk factor (HRF) is the third risk evaluation measure. This component is based on the historic navigation patterns in the area of interest (obtained from the historic automatic identification system (AIS) data), with a focus on finding the possible near-miss collisions between vessels. As the near-miss collisions have rarely (or not at all) been documented, the approach used in this paper finds the theoretical NMC points based on the intrusion of a ships' domain. For this purpose, historic AIS data for the area of interest are used to detect potentially dangerous (high risk) locations on waterways. The following section describes AIS data, the near-miss collision frequency estimation and a method for finding the historic risk along the path.

#### 3.3.1. Automatic Identification System

Automatic identification system (AIS) is a tracking tool that gathers data about different vessels' identity, speed and course in the vicinity [35]. The geographical area of interest in this research is Trondheim fjord and its waters. Therefore, an AIS dataset containing historic data in this area was acquired from the Norwegian Coastal

Administration (NCA)[1]. Some useful parameters from this dataset that can aid geometric collision risk assessment are speed over ground (SOG), course over ground (COG), true heading, navigation status, rate of turn (ROT), calculated speed, ship length, longitude and latitude. An important thing to note is that, due to the specifics of AIS, data are typically received by several base stations at the same time. However, these base stations are not synchronised in time. Hence, the same "observation" may be included in the dataset with two different timesteps.

Use of the AIS data for near-miss collision detection requires some pre-processing:

1. separating and storing data about each vessel,
2. cleaning data — (i) sorting in ascending order based on timestep, (ii) removing records with navigation status "moored" ($nav\_status = 5$) or "aground" ($nav\_status = 6$),
3. separating different routes of the same ship to avoid incorrect interpolation of missing data for large resting intervals,
4. interpolating the AIS data within each route to fill in for the missing timesteps (10 second intervals are used here).

The reason for excluding vessels based on their navigation status is that this research focuses on vessels in motion and their close encounter situations. An example of interpolated trajectories of different vessels in the fjord based on AIS data is demonstrated in Fig. 4.

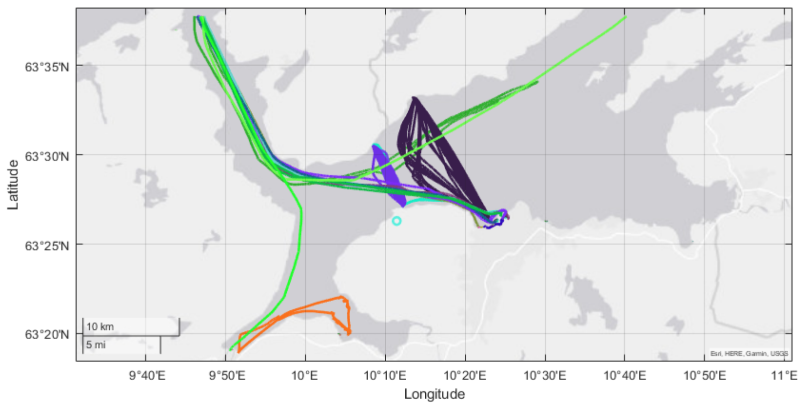


**Figure 4.** Historic AIS data trajectories (after interpolation) of different vessels on one day, plotted on the geographic map in Trondheim fjord area.

When working with the AIS data, some missing or incorrect values were encountered. For example, in a few cases, the reported ship length is equal to zero. In these situations, some assumptions have to be introduced to deal with erroneous data. However, in such cases, the safety domain overlap method might not give as precise results anymore. "Jumping" position is another issue observed in the data. In this case, some data are missing that give information about how the vessel got from one location to another after a longer time. This was solved by separating the data into multiple trips of the same vessel to avoid incorrect data interpolation between those locations.

### 3.3.2. Near-miss collision estimation

There are several ways to estimate near-miss collisionsbetween two encountering vessels. In this paper, the author focuses on NMC estimation based solely on the safety domain intrusion / overlapping, similar to Grossmann [31]. In this method, several

[1] https://www.kystverket.no/en

shapes of ship domain $\mathcal{D}$ could be used. A review of different ship domains is given in Szlapczynski and Szlapczynska [36]. For the sake of simplicity, a circular safety domain is used in this research, with radius depending on the ship length $l_s$ (obtained from the AIS data): $\mathcal{D} = f(l_s)$. The steps of finding NMC points are:

1. *safety domain overlap* investigation at each timestep using equirectangular projection distance between vessels, and
2. *midpoint calculation* for each overlap case (to find the collision point).

First, the safety domain overlap is investigated by calculating the distance between the two geographical coordinates $(\varphi_1, \lambda_1)$ and $(\varphi_2, \lambda_2)$, where $\varphi$ represents latitude and $\lambda$ is longitude of vessels' location, using equirectangular projection based on Pythagoras' theorem. Although the Haversine formula would give a better precision when calculating the great-circle distance $d$ between two points, it is computationally more expensive than the equirectangular approximation. Therefore, in this case, when distances between the NMC vessels are relatively small, the author prefers using the latter method to speed up the calculation time.

In the situations when the safety domain intrusion is detected, the historic NMC point is calculated as the midpoint $(\varphi_m, \lambda_m)$ between the two vessels. The output of the AIS data processing is a list containing the NMC points.

#### 3.3.3. Historic risk along the path

To find the *historic risk* on the path, the previously obtained list of the NMC points in the area is used. At each timestep of the path, the distance $d_{NMC_{cl}}$ from the vessel to the closest NMC point is calculated. If this point is within a pre-defined threshold range *thres* from the vessel, then the historic collision risk is calculated linearly to gain the historic risk value in range $[0, 1]$, where the lower value represents lower risk:

$$r_{hist} = \begin{cases} \frac{1-d_{NMC_{cl}}}{thres}, & \text{if } d_{NMC_{cl}} \leq thres \\ 0, & \text{otherwise.} \end{cases} \tag{10}$$

### 3.4. Total collision risk using fuzzy inference system

The three above-mentioned risk factors, static risk ($r_{stat}$), dynamic risk ($r_{dyn}$) and historic near-miss collision risk ($r_{hist}$) are combined to obtain the *individual collision risk value* $\mathcal{R}_n$ at every timestep $n$:

$$\mathcal{R}_n = f(r_{stat}, r_{dyn}, r_{hist}). \tag{11}$$

The *total collision risk* evaluation score $\mathcal{R}_{total}$ is obtained applying root-mean-square (RMS) method on all the individual collision risk values along the traversed path:

$$\mathcal{R}_{total}(\rho) = \sqrt{\frac{1}{n}(\mathcal{R}_1{}^2 + \mathcal{R}_2{}^2 + \cdots + \mathcal{R}_n{}^2)} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\mathcal{R}_i{}^2}. \tag{12}$$

This is repeated for every path $\rho$ in the scenario. See a general flowchart of this process in Fig. 5.

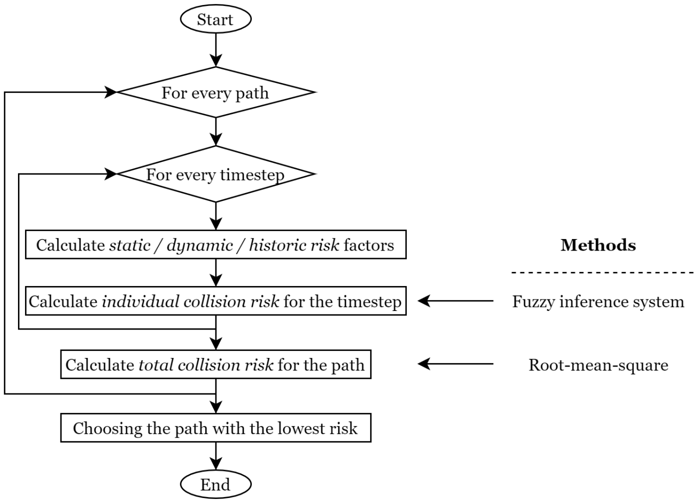


**Figure 5.** Flowchart of the total risk calculation for each path and corresponding methods used.

### 3.4.1. Fuzzy inference system

The individual risk of collision is calculated at every timestep using a fuzzy inference system (FIS) that is based on expert knowledge. The Fuzzy Logic Toolbox[2] in Matlab is used for modelling FIS. The designed multiple-input and single-output (MISO) system is a Type-1 Mamdani FIS with three inputs (static / dynamic / historic risks), one output (individual risk value) and twenty-seven rules in the expert rule base (see Fig. 6).

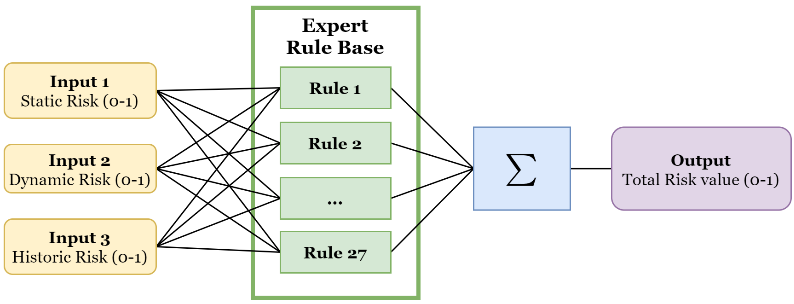


**Figure 6.** Fuzzy inference process.

### 3.4.2. Membership functions

All the input variables have the same shape of membership function with three linguistic states (values) — *low* (L), *medium* (M), and *high* (H) (see on the left side in Fig. 7). The output, however, has four linguistic states — *low* (L), *medium* (M), and *high* (H) and *very high* (VH) (see on the right side in Fig. 7).

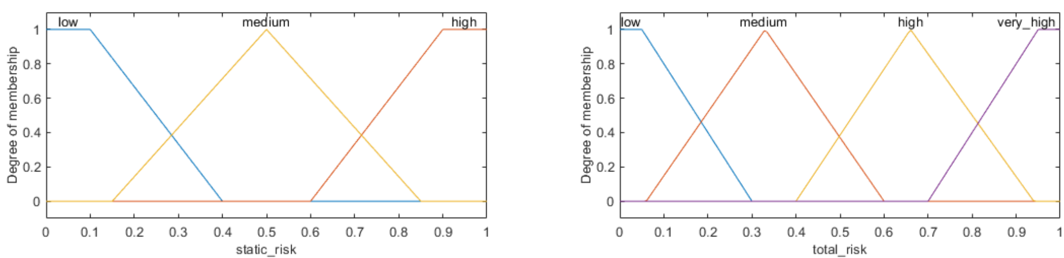


**Figure 7.** Membership functions of the FIS of input static risk (left) and output total risk value (right).

[2] https://se.mathworks.com/help/fuzzy/fuzzylogicdesigner-app.html

#### 3.4.3. Expert rule base

Fuzzy rule base has been developed based on a group of experts' knowledge. The experts invited to take part in this research are experienced mariners and maritime training simulator instructors from Norway with over 10 years of experience. The fuzzy reasoning rule base is given in Table 2.

**Table 2.** Expert rule base of the total risk value based on nautical experts' knowledge.

| | | $r_{static}$ $(r_{historic} = L)$ | | | $r_{static}$ $(r_{historic} = M)$ | | | $r_{static}$ $(r_{historic} = H)$ | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | L | M | H | L | M | H | L | M | H |
| $r_{dynamic}$ | L | L | L | M | L | M | M | L | M | M |
| | M | M | M | H | M | M | H | M | M | H |
| | H | M | M | VH | M | H | VH | M | VH | VH |

Based on the obtained expert rule base, the generated surface plot is demonstrated in Fig. 8. This plot shows the relation between two input variables (static risk and dynamic risk) and the output total collision risk value.

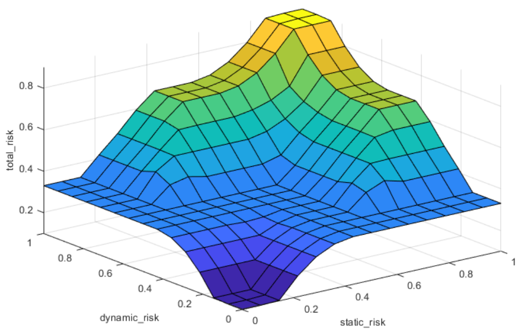


**Figure 8.** Surface plot of the FIS based on the expert rule base, showing dependency of the total risk on the dynamic and static risk inputs.

In order to implement the system, all the input values are normalised to the range $[0, 1]$. It is possible to tune fuzzy membership function parameters and extend the rule base using different tuning methods, such as GA, PSO and others.

## 4. Simulation and results

An open-source maritime platform named Autoferry Gemini [37] based on Unity game engine is used for the simulations of autonomous ships' navigation scenarios (see Fig. 9). Simulation of ship navigation scenarios and calculation of the necessary ship interaction parameters is performed in Gemini. Additionally, MATLAB[3] is used for calculation of individual risk factors, the total collision risk estimation using FIS, AIS data processing and data visualisation. The architecture of the framework is presented in Fig. 10.

[3] https://www.mathworks.com

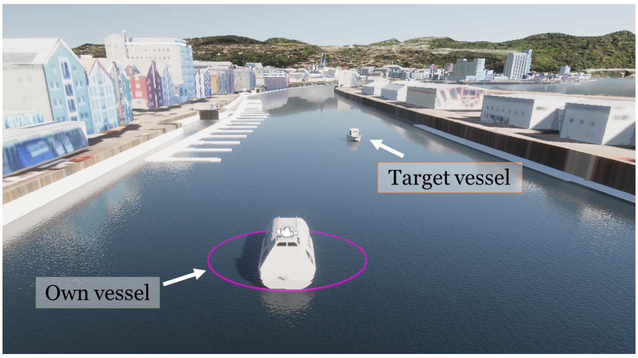


**Figure 9.** The own vessel navigates in a head-on encounter situation with another target vessel in the Trondheim channel. Screenshot from the Autoferry Gemini simulator.

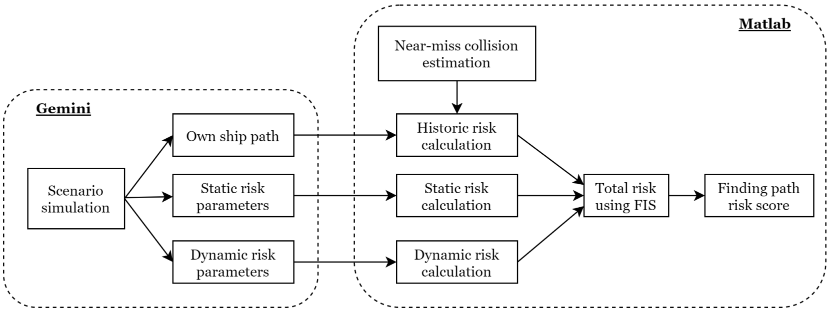


**Figure 10.** Architecture of the simulation framework.

Simulations were executed using Unity 2019.4.21f1 on an Intel i7 with hexa-core processor. Risk calculations and fuzzy system were executed in MATLAB R20201a. The own ship model used in simulations is the *Njord vessel* —- an 11 meter long retrofitted lifeboat model inspired by Ocean Space Drone by Kongsberg Seatex (see Fig. 11). The target ship in the simulator is chosen to be a 7.51 meter long cabin cruiser *Havfruen V* motorboat (medium-sized boat) model [38].

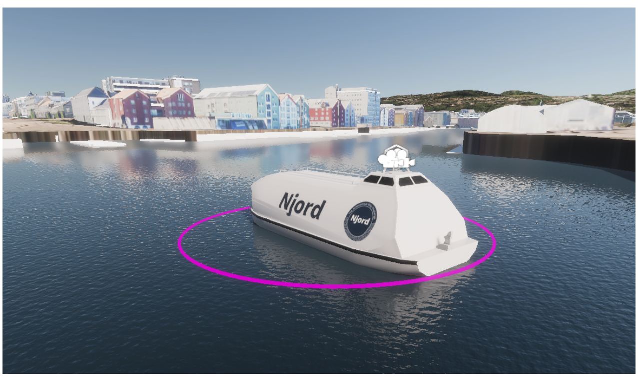


**Figure 11.** Njord vessel in the Autoferry Gemini simulator.

When working across platforms, it should be noted that the historic AIS data are provided in geographic coordinate system (GCS), while parameters extracted from Unity are in Unity units. A conversion between the coordinate systems has to be performed where necessary.

The Gemini simulator includes a few existing scenarios of ship navigation that are based on real-ship collected data (see description of the dataset collection in Chapter 3 in Vasstein [38]). The scenario data collection took place in Ravnkloa in Trondheim, Norway, on 15th of September 2020. It was of high interest of the author to test the proposed method in three different navigation situations. Therefore, for validation purposes, three scenarios from Gemini, number 5, 8 and 9, were selected as the validation test setups. In all scenarios, the total risk value is calculated for the path of the Njord vessel (OS). For each test case, additionally to the original OS path (path A), three derived paths were generated — a cautious path (B) and two incautious paths (C and D). This allows to compare four different OS path risk values for each scenario. Path B is a path where the OS keeps cautious distance to both static and dynamic obstacles in the vicinity. Here, path C is a path where safety in regard to static obstacles is compromised. That means the OS chose to navigate from the start position to the end position without keeping a cautious distance to the static obstacles. As for path D, it comprises a relatively dangerous manoeuvre of the OS with navigation in the direction of TS and a last minute collision avoidance. It is worth noting that in all test cases, the TS keeps its trajectory, however, only the OS path is altered.

### 4.1. Test case 1

*Scenario 8* is presumed as the test case 1. It is a head-on encounter passing scenario (see Fig. 12).

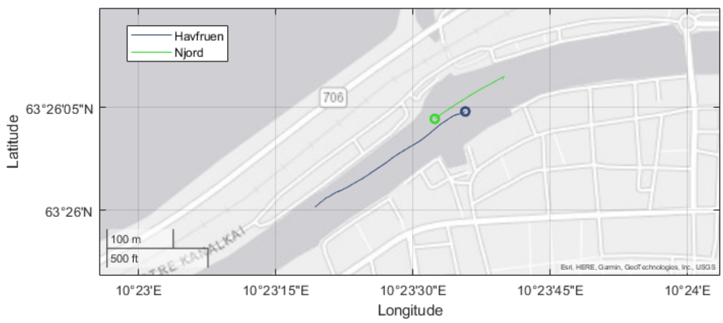


**Figure 12.** Test case 1 — head-on passing encounter. The circle depicts the end position.

In this situation, Njord vessel is assumed to be the own ship (OS), whereas Havfruen is the target ship (TS). The original *path 1-A* represents the real path. For the generated *path 1-B*, the OS is traversing a cautious path. Here, that includes keeping a larger distance from the target ship when passing it and the land (static obstacle), as well as performing an obvious avoidance collision avoidance manoeuvre early in time. For the generated *path 1-C*, the OS follows a more incautious path in regard to distance to static obstacles (closer to the land) but still avoiding the TS and reaching the goal position. The generated *path 1-D* is similar to the path C, however, this path is more incautious in regard to dynamic obstacles. Here, an incautious path is a path where the OS keeps its head-on direction towards the TS and performs a collision avoidance manoeuvre in the last moment passing the TS with a small distance in-between. This is an attempt to represent a potentially dangerous situation that could arise in a narrow channel.

The resulting total risk values for each path scenario, using three different CRI functions, are provided in Table 3. Additionally, a mean total risk value ($\mu$) and deviation ($\sigma$) for each scenario are calculated. The resulting values are visualised in Fig. 13.

**Table 3.** Total risk value in test case 1 for four OS paths using three different CRI methods.

| | Total risk value | | | | | |
|---|---|---|---|---|---|---|
| Path | $CRI_1$ | $CRI_2$ | $CRI_3$ | $\mu$ | $\sigma$ | $\sigma(\%)$ |
| 1-A | 0.3305 | 0.3308 | 0.2329 | 0.2981 | 0 | 0 |
| 1-B | 0.3234 | 0.3238 | 0.2154 | 0.2875 | -0.0105 | -3.53 |
| 1-C | 0.5262 | 0.5266 | 0.3599 | 0.4709 | 0.1728 | 57.98 |
| 1-D | 0.3435 | 0.3432 | 0.2412 | 0.3093 | 0.0112 | 3.77 |

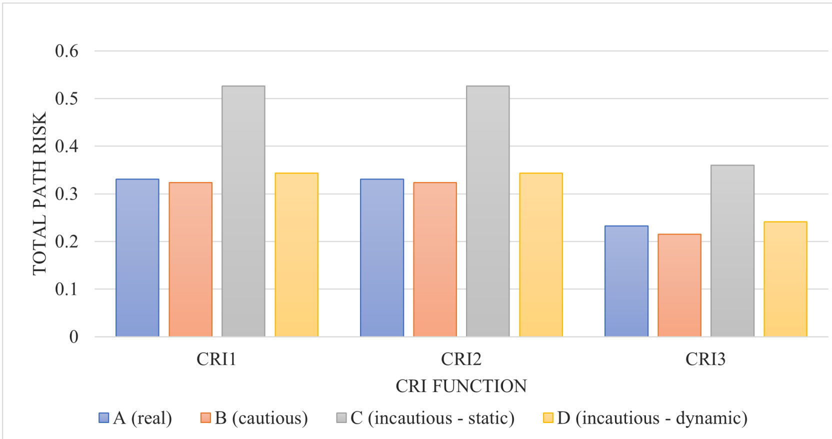


**Figure 13.** A plot showing resulting total risk values for four scenarios of the test case 1, using three different CRI methods.

## 4.2. Test case 2

*Scenario 9* in Gemini is chosen for the test case 2. This is a situation where OS enters the channel from the direction under the bridge and avoids the TS navigating in the channel (see Fig. 14).

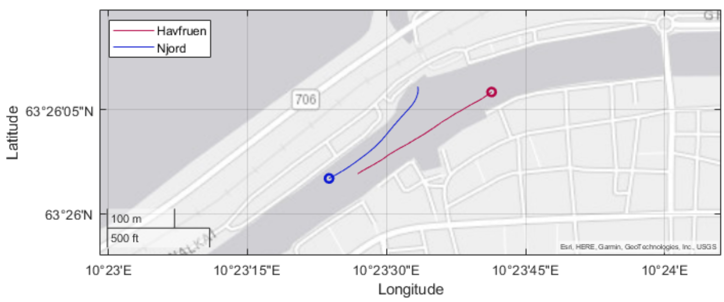


**Figure 14.** Test case 2. The circle depicts the end position.

Also for this test case, three new paths were generated based on the same aforementioned principles — 2-B, 2-C and 2-D. The resulting risk values for each path are presented in Table 4 and visualised in Fig. 15.

**Table 4.** Total risk value in test case 2 for four proposed scenarios using three different CRI methods.

| Path | Total risk value | | | | | |
|---|---|---|---|---|---|---|
| | $CRI_1$ | $CRI_2$ | $CRI_3$ | $\mu$ | $\sigma$ | $\sigma(\%)$ |
| 2-A | 0.4138 | 0.4062 | 0.4025 | 0.4075 | 0 | 0 |
| 2-B | 0.3864 | 0.3531 | 0.3800 | 0.3732 | -0.0343 | -8.43 |
| 2-C | 0.4969 | 0.4244 | 0.4431 | 0.4548 | 0.0473 | 11.61 |
| 2-D | 0.4186 | 0.3402 | 0.3772 | 0.3787 | -0.0288 | -7.08 |

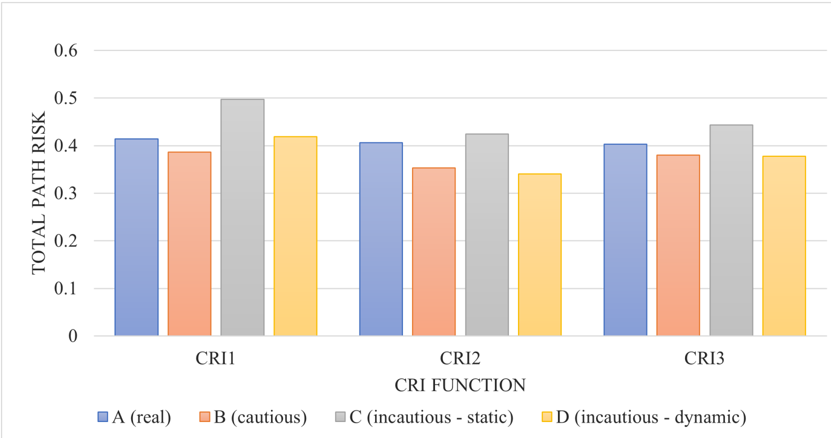


**Figure 15.** A plot showing resulting total risk values for four scenarios of the test case 2, using three different CRI methods.

### 4.3. Test case 3

Finally, the test case 3 is based on *scenario 5* in Gemini. This head-on encounter scenario differs from the previous for the reason that here TS is mostly keeping its position static. Its motion is most probably only affected by the water movement. Its position is still changing slightly, so the extended risk calculation method still considers it as a dynamic obstacle that provides danger to the OS. Here, OS navigates in the channel and encounters an almost standing TS in a head-on situation (see Fig. 16).

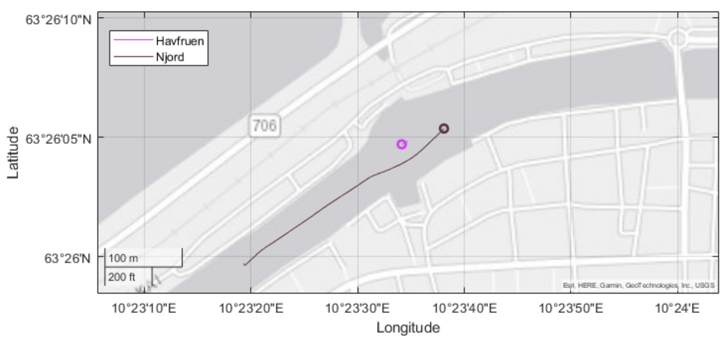


**Figure 16.** Test scenario 5. The circle depicts the end position.

In this test case, three new paths were generated based on the aforementioned principles — 3-B, 3-C and 3-D. The resulting risk values are shown in Table 5 and visualised in Fig. 17.

**Table 5.** Total risk value in test case 3 for four proposed scenarios using three different CRI methods.

| | Total risk value | | | | | |
|---|---|---|---|---|---|---|
| Path | $CRI_1$ | $CRI_2$ | $CRI_3$ | $\mu$ | $\sigma$ | $\sigma(\%)$ |
| 3-A | 0.3298 | 0.3274 | 0.2213 | 0.2928 | 0 | 0 |
| 3-B | 0.3419 | 0.3417 | 0.2143 | 0.2993 | 0.0065 | 2.21 |
| 3-C | 0.3855 | 0.3853 | 0.2973 | 0.3560 | 0.0632 | 21.58 |
| 3-D | 0.3297 | 0.3294 | 0.2117 | 0.2903 | -0.0026 | -0.88 |

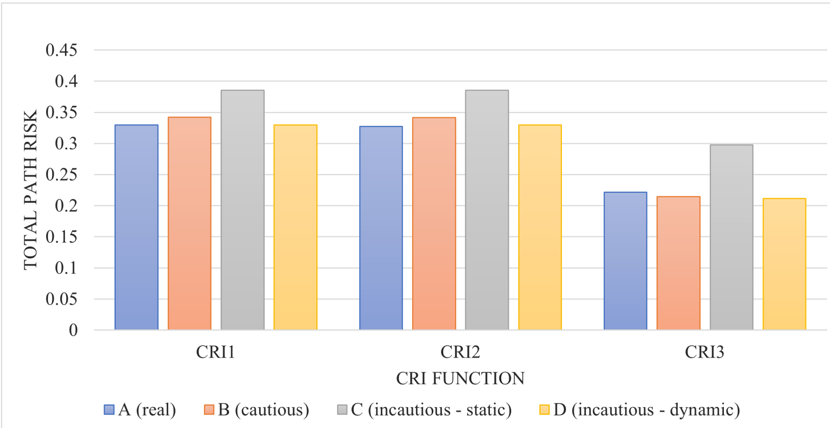


**Figure 17.** A plot showing resulting total risk values for four scenarios of the test case 3, using three different CRI methods.

### 4.4. Results

Simulation results are discussed focusing on two aspects: (i) risk values of the generated cautious / incautious paths (B, C and D) compared to the original path (A), and (ii) comparison of risk values when using different CRI functions. For the former aspect, deviation parameters $\sigma$ and $\sigma(\%)$ for each path in all test cases were calculated, presuming the original path as the benchmark.

The results demonstrate that, in test cases 1 and 2, *path B* (cautious path) presents a decrease in the total risk value (3.53% and 8.43% respectively), however, in the test 3rd test case, path B has increased by 2.21%. This result highlights that an attempt to improve the safety of the planned path (when that is possible), in terms of collision with static and dynamic structures, leads to decreased total risk on the path according to the calculation method proposed in this article. However, the increase of the total risk value for path 3-B could be attributed to several factors, as difficulty to improve the original path when it is already cautious, the specifics of the three chosen CRI calculation methods, tuning of the method parameters, and the specifics of the navigation situation in the test case 3, to name a few.

Superior results are demonstrated for *path C* where the vessel avoids the TS by navigating closer to the static obstacles. Here, a significant increase in the risk value ($\sigma$ is 57.98%, 11.61% and 21.58% for setups 1, 2 and 3, respectively) is observed in all three test setups. This indicates that the proposed method responds well to the increased risk of grounding and stranding.

The risk values of *path D* in all three test cases show varying results. A slight improvement ($\sigma = 3.77\%$) is demonstrated in a head-on encounter scenario in test case 1. However, in test cases 2 and 3, the total risk value has decreased by 7.08% and 0.88% compared to the original path. The simulation observations and results analysis indicate that in some cases when the dynamic risk factor has been increased (due to the more dangerous situation in terms of the TS), the static risk factor decreases, thus leading to a lower total risk value.

The comparison of the total risk value for different chosen CRI methods demonstrates that $CRI_1$ and $CRI_2$ provide similarly looking results for test cases 1 and 3. The similarity between test cases 1 and 3 is found in the type of direct head-on encounters scenarios. This could indicate that for head-on encounter scenarios, when the ship headings are changing slightly, $CRI_1$ and $CRI_2$ respond similarly. However, in test case 2, no specific pattern is observed. A larger number of scenarios should be tested to provide clearer conclusions about the use of CRI functions.

## 5. Discussion

Simulation results reveal that the static risk component has a great impact on the total risk value. The author speculates that this has led to a result that in some cases, a theoretically incautious path demonstrated a decrease in the total risk value, and opposite cases when a theoretically cautious path had a slight increase in the total risk value. Another reason could be that the generated paths for each test setup were following simple principles described above of what a cautious / incautious path in different scenarios would look like. However, this research would benefit from validating these generated paths by a group of experts.

It is worth also discussing the interesting findings revealed when consulting with nautical experts. Based on the experts' judgement, out of all the proposed risk factors, static risk has a higher importance than the dynamic risk. An explanation could be that in Norway, a large portion of the marine accidents is connected with ship grounding on the hard coastal rock in Norway. This type of risk is the "invisible danger", as it is often difficult to foresee. In contrast, when two ships are navigating in a close vicinity, both of them are responsible for taking actions to avoid a collision. Additionally, according to experts, weather and environmental conditions have a large impact on the total risk value and this should be considered for future work. Another aspect that could be included as part of the dynamic risk is the ship type. Finally, the experts came to an agreement that the historic risk has the least impact on the total risk value in the proposed method.

One limitation of this method could be that the test scenarios consider only two vessels encounter situations. How would the results change when dealing with a multi-vessel collision avoidance? A solution here could be to adapt a vessel conflict ranking operator (VCRO) proposed by Zhang *et al.* [32], or an improved version of the method (NVCRO) [39]. This research has arisen a few other ideas for improvement and questions. Tuning the fuzzy system parameters using an adaptive neuro-fuzzy inference system (ANFIS) might improve the calculation of the total risk value. Another alternative would be to use other tuning methods, such as genetic algorithm (GA) or particle swarm optimisation (PSO) for tuning of the membership function parameters. Another question is, how does the navigation risk changes for different navigation modes, e.g. (un)docking? The proposed method currently does not differ between navigation situations. Therefore, the total risk value will be obviously higher when the vessel is (un)docking or navigating in a narrow pathway / channel, even though it is the intended action. However, in such case, the vessel and its planned path should not be penalised as much, as it is an intentional action and the CRA method should be more tolerant. The consultation with the nautical experts turned out to give additional insight into the problem. With this in mind, in the next stages of the simulator development, it would be useful to get feedback from nautical experts on the risk assessment decisions in various scenarios and for feedback on the generated scenarios. Finally, a question that has been around since the first stages of this research is, how fair is it to assess parameters of the path if the path planning / collision avoidance algorithm has made an uninformed choice when performing planning? This leads to an idea that the proposed CRA method could as well be incorporated as part of these algorithms to improve their outcome from the safety perspective.

This research has opened several future research directions for improving the proposed method, such as:

- extending the fuzzy system with additional risk factors that assess environmental conditions, COLREGs, compliance with good seamanship, etc.,
- extending the risk assessment model by including consequences (cost) of different incident outcomes (such statistics could be based on insurance company data),
- using nautical experts' knowledge to receive feedback on how realistic generated scenarios in simulator and the planned paths are,
- using nautical experts' knowledge to identify conditions for improved near-miss collision detection in real-life scenarios.

In order to test the proposed method more extensively, a number of navigation algorithms should be tested in the simulator and their paths evaluated and compared.

## 6. Conclusions

In this article, the author has proposed and tested an extended collision risk assessment method for evaluating autonomous ship navigation paths by combining several risk factors using a fuzzy inference system. The method considers static, dynamic and historic risk factors as part of the total risk value. Here, the historic risk factor is based on the near-miss collision calculation from the historic AIS data. The calculated total collision risk for each path allows for comparing the safety of these paths and choosing the least risky one. The proposed method was validated in three test setups, and the results were analysed using the Gemini simulator combined with MATLAB. The test simulation compared risk values of the original path, cautious path, and two incautious paths. Results show that the proposed extended collision risk assessment method is able to assign higher risk values to more dangerous paths and lower risk values to safer paths. The method assigns special attention to collision risk with regard to static obstacles. On the other side, one could argue that the extended CRA method does not consider the complete picture of the navigation situation. The author is confident enough to say that the proposed method is satisfactory to assess collision risk in good weather conditions and could be supplemented with multiple other risk factors in the future. The Gemini simulator and ESP itself have a great potential, opening doors for more extensive testing and experimentation, including tuning the existing methods or complementing them with new methods.

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**Conflicts of Interest:** The author declares that there are no conflict of interest.

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# E

## Paper A5

# On the use of maritime training simulators with humans in the loop for understanding and evaluating algorithms for autonomous vessels

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**Abstract.** The prospect of a future where the maritime shipping industry is dominated by autonomous vessels is appealing and gaining global interest from industry majors, research institutions, and academia. Potential advantages include increased operational safety, reduced costs, and lower environmental footprint. However, the transition will not happen overnight and is not without challenges. For example, algorithms for autonomous navigation must take into consideration safety concerns of the own ship, its crew and passengers, other surrounding ships, and the surrounding environment. This raises a need to test and verify safety, performance, and robustness of the algorithms responsible for the autonomous functionality. In addition, the transition towards fully autonomous ships is likely to be gradual and involve remote control centres and ships with varying degrees of autonomy. Hence, humans will inevitably have to interact with autonomous vessels in a variety of scenarios, including overriding own ships from land or on board, as well as communicating with autonomous ships from other fleets. Inevitably, full scale scenario testing involving real vessels and humans is costly, impractical, time-consuming, and potentially dangerous. In this paper, we propose an alternative approach, and explore how maritime navigation training simulators with humans in the loop can be used as a testbed for understanding and evaluating algorithms for autonomous vessels. In the proposed setting, we can directly compare choices made by an algorithm with those of a skilled human navigator for a variety of navigational tasks. Moreover, we can study in real-time the behaviour and decision-making of human navigators in mixed scenarios that also include autonomous ships, whether this is known beforehand or not. Our paper provides an overview of related work, details on maritime simulators and how algorithms can be tested, and some of the technical requirements. To exemplify our approach, we present two example test setups, and provide a brief discussion of our findings. We conclude that using maritime training simulators enables the study of several interesting and vital research questions, including that of the interaction between autonomous and traditional vessels operating side by side.

## 1. Introduction

With autonomous ships on the horizon that may affect the safety of the own ship and other ships, its crew and passengers, and the surrounding environment, the need to test and verify the safety, performance and robustness of the autonomous functionality is a top priority. Autonomous ships therefore require sophisticated sensors and algorithms to collect and fuse information about the ship and its surroundings to form an adequate situational awareness. Based on the situational awareness, an advanced navigation algorithm[1] must be able to automatically change the ship's route and perform collision avoidance manoeuvres, ensuring safe sailing in compliance with rules and regulations. Lack of unambiguous specifications is also a challenge for an autonomous ship, since current regulations, including The Convention on the International Regulations for Preventing Collisions at Sea (COLREG) [1], use expressions which require interpretations, such as ample time, good seamanship, safe speed, etc. For an overview of relevant intelligent autonomous navigation algorithms, see [2].

Due to the complexity of navigating a vessel, traditional algorithms from control engineering and other classic fields can easily come up short, with algorithms from the field of artificial intelligence (AI) such as deep neural networks, evolutionary algorithms, and reinforcement learning tending to be better choices. However, AI-based algorithms and particularly machine learning algorithms often suffer from a lack of explainability or interpretability, and they may also be inherently complex. As a consequence, testing such algorithms quickly becomes a complex problem in itself. Full scale realistic testing of algorithms employed on a real ship is inevitably going to be costly, dangerous, impractical and probably not even allowed without thorough testing in a safe environment in advance. Two existing testing approaches are: (i) simulation-based testing and (ii) functionality-based testing. In this paper, we discuss and focus on the simulation-based testing approach. A procedure for simulation-based verification of autonomous navigation systems is proposed in [3]. The verification and assurance of machine learning algorithms needs to be fundamentally different from traditional assurance and verification processes based on requirements and physical understanding [4, 5, 6, 7]. Moreover, since autonomous vessels will have to relate to traditional vessels with humans onboard and vice versa, the human dimension becomes very important.

There are several ship simulators, e.g., [8, 9, 10], that could enable us to test path planning and collision avoidance scenarios but as described later in this article, there are many challenges that require more advanced setups. For example, in order to evaluate interactions with humans, there is a need for a very realistic setup. Likewise, algorithms could be tested by simulating data from the automatic identification system (AIS) during realistic navigation scenarios but the lack of a visual model for the AIS-simulated vessel will impact the human navigator's decision-making. It will therefore be of limited value to study the human navigator's actions towards an invisible AIS-simulated "ghost ship."

Due to humans' ability to learn and adapt to new and unexpected situations, humans can play an important role in complex technological systems such as autonomous navigation to ensure safe and efficient operation [11]. Testing how human navigators will react to an autonomous vessel piloted by an algorithm in real life is one of several interesting research questions. It could also be valuable to compare how well an algorithm solves a given set of scenarios compared to a human navigator.

In this article, we argue that the use of maritime training simulators will enable testing and research that is otherwise very difficult to perform, and propose to use these simulators as a testbed to investigate research questions similar to the above. The proposed test setups could aid in evaluating how well algorithms for autonomous vessels perform in general and especially with humans in the loop. We suggest looking both at a setup when an intelligent algorithm is controlling target ship(s) in the simulator, and a setup where an intelligent algorithm is controlling the bridge and executing navigation tasks. Another benefit of using a simulator for these experiments is the ability to control the experiment and making sure that the situations can be replicated.

[1] In this paper, the word 'algorithm' may also refer to several algorithms combined and used together, or an autonomous system as a whole.

The remainder of the paper is organized as follows: Related work is reviewed in Section 2. Section 3 provides an overview of existing maritime simulators, their history and possible simulator setups. Testing of autonomous algorithms is described in Section 4. Section 5 presents technical requirements for the proposed use cases. Different test setups are proposed in Section 6. Section 7 contains a discussion, and finally, some concluding remarks are drawn in Section 8.

## 2. Related work

Autonomous vessels are already investigated using various simulators. However, using *maritime training simulators* normally used in education of cadets, as proposed in this paper, is a novelty. Performing tests in maritime training simulators enables a means for verifying autonomous navigation systems or path planning algorithms, with humans in the loop, in a safe simulated environment before implementing them on a real vessel at sea.

A maritime training simulator that could fulfill this purpose is the K-Sim simulation platform developed by Kongsberg Digital, certified by DNV and fulfilling Standards of Training, Certification and Watchkeeping (STCW) requirements. Its intended purpose relates to virtual prototyping, testing, and verification of autonomous algorithms for vessels [12]. This includes scenario generation faster than real-time, energy consumption predictions, taking into account environmental conditions, and route verifications. Another use case of the platform is simulation-based prediction, as well as using live data from a ship and its environment.

In another project, Wärtsilä delivered a navigation simulator and specific mathematical models for Intelligent Shipping Technology Test Laboratory (ISTLAB) at the Satakunta University of Applied Sciences (SAMK) in Finland [13]. The goal of that project, launched in early 2019, was to develop a testing environment for remotely controlled, autonomous vessels.

With a focus on simulation-based verification of autonomous navigation systems, Pedersen et al. [3] propose to use a digital twin for testing purposes. A complete test system includes scenario manager, test evaluation module, operating environment, test interface, and digital twin that represents the systems of the own ship. The authors indicate that the Open Simulation Platform (OSP) [14] may potentially be used later for testing purposes.

Finally, we draw attention to research by Vagale et al. [15], who focus specifically on the evaluation of path planning algorithms from the risk and safety perspective.

## 3. Maritime training simulators

Maritime simulators for training can perhaps be labelled "very serious games." These simulators have a very realistic touch and feel since they typically have a vessel bridge replica with large screens with a wide view angle, all essential handles and equipment found on board a real ship, and often even an audio system that provides realistic sounds. This very realistic physical setup combined with strict rules on expected behaviour, and maybe even combined with use of uniforms, makes it possible to create a theatre-like atmosphere that is immersive and blur the lines between simulator and real life. Indeed, the provided training in these simulators is considered realistic enough that, according to International Maritime Organization [16], cadets are permitted to fulfil part of their training in a simulator.

Although marine training simulators may seem realistic to human navigators, it cannot be assumed that the simulators are sufficiently realistic for testing a particular class of autonomous vessel functionality, namely that of object detection and classification. Hence, this functionality cannot be directly implemented in the simulators. To overcome this challenge, authors in [17] propose utilising Cycle-Consistent Adversarial Networks (Cycle-GANs) to transfer the simulator data to a real-world-like environment before autonomous functionality such as object detection and classification is performed.

### 3.1. History

Technically sophisticated simulators are in particular found in the training of professionals where one seeks to increase safety, such as aviation, shipping, and healthcare [18]. The earliest ship bridge simulators with visual night scenes were introduced in the 1970s [19] and full bridge simulators have already been commercially available for decades, reaching the point where the international rules and regulations as prescribed by the International Maritime Organization (IMO) mandates the use of simulator training as a basis for certifying professional navigators through its STCW guidelines.

The 2010 amendments of the STCW 1978 code section A-I/12 added requirements for its member states to include simulator-based training with modern technology like electronic chart displays information system (ECDIS), AIS, and dynamic positioning (DP). The updated codes also define that seafarers may demonstrate their competence to handle a ship in all conditions through approved simulator training while at the same time providing the nautical student with limited credit as an equivalency for sea-going service depending on factors comprising the level of simulation and scenarios, time spent, student-teacher ratio, pre-brief and de-brief procedures, and integration with other elements in the approved training program [16]. The STCW requires the approval of simulators used for mandatory training or assessment of seafarers, and classification societies often do the travail of simulation certification. Det Norske Veritas (DNV) for instance has developed a standard for certifying simulator compliance, where they also define four classes of bridge operation simulators, Class A, B, C and S, where only Class A, full mission simulator, meets the IMO requirement of "manoeuvre and handle a ship in all conditions" demanded for approval of sea-time equivalency [20].

### 3.2. Major vendors

Major vendors of full mission maritime training simulators in accordance with STCW 2010 are:

- K-SIM by Kongsberg Digital [8]
- NTPRO 5000 by Wärtsilä [9]
- NAUTIS by VSTEP [10]
- SIMFLEX by FORCE Technology [21]
- BOREALIS by Poseidon [22]
- REMBRANDT by BMT [23]
- ARI SMS by ARI Simulations [24]
- IS FMBS by Image Soft [25]
- ANS6000 by Rheinmetall Electronics [26]

### 3.3. Simulator setup

Typically, a simulator setup consists of at least two or more rooms (one-to-many setup). Firstly a room where the main instructor controls the exercise, configures the training scenario, selects vessel types and sizes, adjusts weather parameters, and more. From this room, the instructor may monitor and record the cadets' performance during the exercise. In simpler cases, a one-to-one simulator with only one navigation bridge connected to the instructor station is also possible (see Fig. 1). An example setup of five navigation bridges connected to a main instructor station is given in Fig. 2.

In addition, the simulator can contain one or more vessel bridge replicas. For simple exercises a single bridge is sufficient, however, both in order to train on more complex challenges and to train more cadets at the same time it is convenient to use several bridges. Typically, the bridges are linked with the same simulation environment, thus allowing the different bridges (simulated vessels) to interact with each other. A picture of a typical training bridge is shown in Fig. 3.

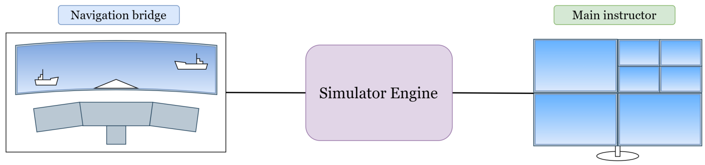


**Figure 1.** Setup of a one-to-one navigation training bridge connected to the main instructor station through a simulator engine.

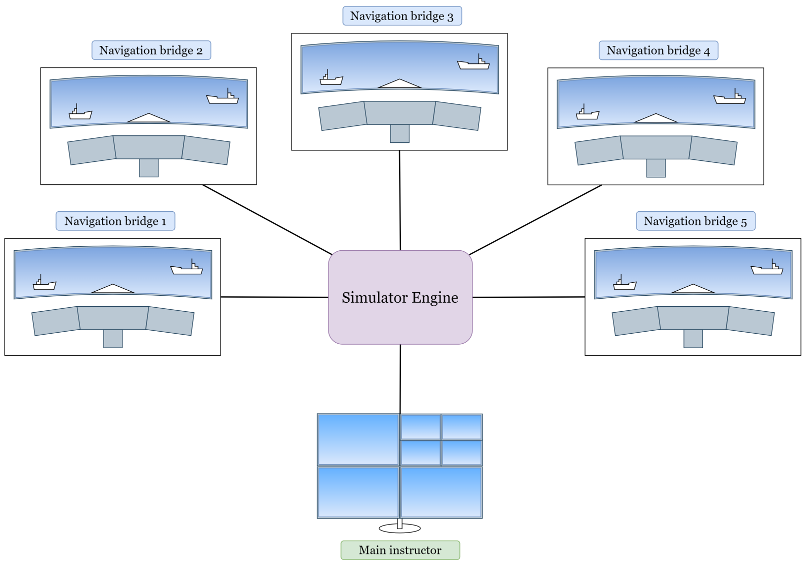


**Figure 2.** One-to-many setup of the main instructor station (in the centre) connected to five navigation training bridges through a simulator engine.

An example of an instructor station overlooking the actions of the cadet navigating the bridge is shown in Fig. 4. A research training simulator is shown in Fig. 5.

*3.4. Target vessels*

In addition to one or more training bridges, the operator or instructor has the possibility to control a number of additional vessels (target vessels) in the training scenario. These vessels have no separate simulator bridge, but are merely vessels, chosen from a library of vessels, that are placed into the simulation environment and given a heading and speed. Throughout the exercise, the operator may adjust these vessels' heading and speed. Later in this paper, we present setups where the target vessels are controlled by autonomous path planning and collision avoidance algorithms.

**Figure 3.** Navigation training bridge at the Department of the Ocean Operations and Civil Engineering at NTNU in Ålesund. Photo: Anete Vagale.

**Figure 4.** Instructor station at the Department of the Ocean Operations and Civil Engineering at NTNU in Ålesund. Photo: Terje Ole Slinning.

**Figure 5.** Research training bridge at the Department of the Ocean Operations and Civil Engineering at NTNU in Ålesund. The research bridge consists of the navigation bridge with controls, three screens (on the right), and the instructor's area (on the left). Photo: Anete Vagale.

## 4. Testing of algorithms

In order to evaluate the performance and capacities of algorithms, extensive testing is required. These tests should be standardized, reproducible, relevant and realistic. As of today, we are not aware of any existing standardized tests for autonomous ships. An attempt at defining requirements for simulator based testing is given in [27]. We expect different actors to develop their own tests before some governing bodies establish some official tests, especially related to safety. However, in addition, there will probably be several other "industry standards" that relate to issues such as efficiency.

### *4.1. Challenges with assurance of machine learning algorithms*

Traditional verification, including the V-model (e.g., see ISO 26262 *Road vehicles - functional safety* in [28]), typically assumes that the requirements of a component are completely specified and that "each refinement can be verified with respect to its specification" [29]. Problems like machine perception and ship navigation cannot be clearly specified. For example, COLREGs [1] that must be complied with when navigating on waters, are in many cases open for interpretation. This has motivated the use of machine learning algorithms which learn from examples rather than being programmed based on a specification [5].

However, understanding and interpreting a machine learning algorithm's reasoning is challenging or even impossible, which makes it challenging to verify the algorithm or to determine when the algorithm's reasoning is in error [30, 31, 32]. Explainable AI (XAI) for algorithms attempts to give a reasoning for the decisions suggested by an algorithm. Additionally, machine learning algorithms are completely dependent on the quality of its training data. Hence, any verification and assurance process needs to include a comprehensive data analysis, documenting if the dataset sufficiently covers the input domain, is representative and complete, particularly regarding corner cases [4]. The choice of resampling strategy, that is, how the data is split into training and test sets using cross validation or bootstrap techniques, must also be evaluated.

The robustness of the algorithms must also be tested and documented. Brandsæter at el. [33] provide an example showing how minor, seemingly insignificant changes like a small image rotation can confuse a classifier. In their example, a one-degree rotation causes a mis-detection of a vessel. It is also shown that when the image is rotated further (three degrees), the algorithm once again correctly detects the vessel, illustrating the unpredictable behaviour of the algorithm. Image manipulations and transformations utilising, for example, Generative Adversarial Networks (GAN) (e.g., [34, 35]) to transform a scene from summer to winter or daylight to night, as well as simple augmentations including rotations, share, blur, and similar (e.g., see [36, 37, 7]) can be utilised to increase the test scope of a limited dataset.

*4.2. Metrics*

The capability and performance of detecting other ships is an essential part of an autonomous ship's situational awareness capability. Relevant metrics for object detection includes number of correctly detected ships (true positives), but also missed targets (false negatives), as well as true negatives and false positives. These numbers are often summarised in other metrics such as precision and recall, sensitivity and specificity, true positive rates, true negative rates, F1-score, etc. But are all targets equally important? Detecting a ship which is far away is less important than detecting a nearby ship on collision course. As the relevance of the different targets depends on the navigation, this should be taken into consideration. Hence, assessing the ship's situational awareness in isolation is not recommended, although methodology for assessing the situational awareness of humans is available, e.g., see [38, 39, 40].

Øvergård et al. [41] argue that existing research is suggestive of limitations of the reliability of subjective assessments, and propose an initial version (prototype) of an automated assessment algorithm for a specific maritime operation. The following control requirements for the safety of navigation, collected based on open interviews with six subject-matter experts who all held deck-officer certifications, were used in the prototype:

(i) distance to land based on own ship length,
(ii) distance to moving objects (vessels) based on own ship length,
(iii) distance to floating objects based on ship length,
(iv) the deviation between ship heading and heading of dock (meaning that the ship should be parallel to the dock during the last part of docking), and
(v) the minimum depth below the ship's keel (the so-called 'safety depth').

The aforementioned parameters can be considered a part of a greater geometric collision risk assessment (CRA) set. More information on metrics for CRA for autonomous vessels, and a comparison of 45 different path planning and collision algorithms, is given in [42].

On the other hand, Vagale et al. [15] propose introducing additional relevant metrics to evaluate path planning algorithms of autonomous surface vehicles (ASVs), such as:

- efficiency / path fitness (e.g. length of path / time used / fuel used),
- compliance with regulations (COLREGs), and
- good seamanship practice.

The above-mentioned metrics are still not clearly defined and in some cases could be overlapping. Typically, compliance with regulations and safety often overlap. Similarly, good seamanship practice requires following COLREGs and vice versa. It is important to look at these metrics in connection with each other; the safest move might be not to move at all, however, that would obviously affect efficiency negatively.

### *4.3. Turing test for autonomous ships*

In addition to evaluating the above-mentioned metrics, interviewing cadets and instructors after the exercise might be useful to capture their experience with the autonomous ship. In this case, it could also be interesting to consider doing blind tests where the cadets and/or instructors do not know which ships are autonomous (similar to Turing's imitation game).

Usually, the cadets train on scenarios where the other vessels (target vessels) are navigated by the instructor. In such a setup, some (or all) target vessels could be autonomous ships. It would then be interesting to see if the cadets notice any difference. An even more interesting scenario emerges from linking several simulator bridges together (see Figure 2) to share a common scene. For a cadet, any observed ship could either be a target ship placed there by the instructor, another ship operated by another cadet(s), or in our case, an autonomous ship. It would be impossible to know without interacting or studying the ship's behaviour.

Finally, it could also be very interesting to do such an experiment in a way that the instructor played the Turing game. Either by letting him / her navigate a simulator bridge instead of the cadet(s), or by manipulating the instructor panel in such a way that there is no way of knowing which ship is autonomous and which is manually steered. This experiment is of great interest because the instructor have years of experience monitoring cadets' navigational behaviour.

How could an autonomous vessel divulge its nature? For one, by performing actions that are contradictory to good seamanship and/or COLREG rules. For instance, several algorithms that have been proposed, e.g., [43, 44], would change heading very often or continuously. This is against COLREG rule 8 since your intentions should be communicated clearly and your manoeuvres should be predictable. This is typically done by navigating in straight lines and making as few heading changes (way-points) as possible. This kind of navigation will often be in stark contrast to many algorithms that focus on optimization and rely on cost or fitness functions. Another way of identifying vessels is radio communication. This is an integral and important part of the cadet's training. Training without the use of radio would usually be seen as out of the ordinary and reduce the quality and immersiveness of the setup. Hence, it could be better to let the instructor or another human to reply on radio on behalf of the autonomous vessel, but it could be a challenge since it would be impossible for a human to accurately predict the algorithm's intentions and relay these truthfully on radio upon request.

## 5. Technical requirements

In order to use a maritime simulator as a test bed for autonomous vessels, it is crucial that the simulator provides an interface that enables third party computers to control various settings and controls in the simulation environment. Below, we have listed some interface properties in order of importance:

- controlling target vessel's speed and heading,
- reading position of fixed and moving obstacles (incl. other vessels),
- controlling (emulating) bridge handles and controls,
- reading bridge view (screen), radar, ECDIS, AIS and other instruments,
- controlling other simulation parameters, such as environmental settings, etc.

Since the designers of the maritime simulators probably did not have this use of the simulators in mind when the simulators were made, there is likely no dedicated interface readily available for this use. However, the features listed above correspond quite well with the needs for the operator/instructor's needs and are probably available through some API or similar used by the software for the operator station. However, existing APIs/interfaces are generally not public and most likely internal to the developer and subject to change. Hence, a crucial element in setting up such a proposed testing environment is access to such an interface, and this most likely depends on close cooperation with and goodwill from the simulator vendor.

## 6. Test setup and research questions

Below, we have listed two main test setups (see Fig. 6) for maritime training simulators and described what kind of interesting research questions these tests could contribute towards answering.

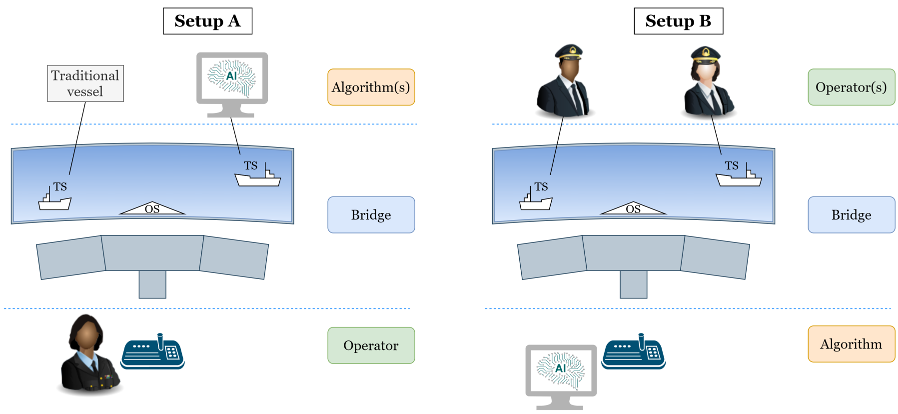


**Figure 6.** Visual representation of the test setups A and B.

- *Test setup A* — where the algorithm(s) control the target vessel(s) while the bridge(s) is/are controlled by human cadet(s).
- *Test setup B* — where the algorithm(s) control the bridge(s).

### *6.1. Test Setup A*

In the first setup (Fig. 6, left), the algorithm(s) control the target vessel(s) and the bridge(s) is/are controlled by human cadet(s) / operator(s). In a mixed environment where traditional ships and autonomous ships co-exist, it is crucial to understand how they may interact. In this test, it is possible to study both how the autonomous vessel(s) responds to the human actions, and how humans react to the actions performed by the algorithm(s). In addition to evaluating the above-mentioned metrics, the cadets may be interviewed after the exercise in order to capture their experience with the autonomous vessel. This setup is suitable to test algorithms similarly to Turing's imitation game.

Another interesting research question is whether it is beneficial for navigators on other vessels to know that the vessel is autonomous? And further, would it be beneficial to know how the algorithm is "thinking"? With explainable AI, it could be possible for an autonomous vessel to broadcast its reasoning and intentions to other seafarers. Could this information be useful, or would it be a distraction? Could it contribute to information overload on humans? On the other side, would other autonomous vessels be able to perform better if they knew the intentions of other autonomous vessels, or could deadlock situations (more easily) occur?

### *6.2. Test Setup B*

In the second setup (Fig. 6, right), the algorithm(s) control the bridge(s). One series of tests that can be performed is to run basic tests of an algorithm with respect to collision avoidance (avoiding fixed and moving obstacles) and even several vessels with identical or different algorithms. These tests can be done with more "Lo-Fi" simulators also, however, these certified simulators may give more reliable results.

A more interesting test is to give the algorithms the same test scenarios that the instructors give the cadets. The instructors have a set of test scenarios they run as part of their training of cadets. An experienced instructor has an excellent reference base on how well humans (cadets) solve the test scenarios. Hence, the instructors should have no problem evaluating how well the algorithm perform compared to humans using the same metrics as they normally do with the cadets. With some minor modifications, it could also be possible to do this test blindly, but the value of that should be weighted against the increased complexity.

Adding another layer of complexity to this test setup, the instructors could compare how well an algorithm performs compared to humans in a situation that could give humans a cognitive overload. One hypothesis could be that humans will outperform the computer in uncomplicated scenarios, however, the computer would be better at handling very complex situations. In addition to answering the aforementioned research questions, the results could also give some insight on the use of algorithms not only to navigate autonomous vessels, but also as decision support tools or as "smart autopilots" on manned vessels.

### *6.3. Other setups*

The suggested setups and research questions above are of course just examples. It is possible to construct numerous different setups by introducing other elements, combining scenarios, etc. Advanced simulators like the maritime training simulators are a great tool that make it possible to do research with humans in the loop and with varying degree of complexity to validate autonomous ship algorithms.

## 7. Discussion

In order to do studies with humans in the loop, it is important to make a test scenario that is as close to reality as possible in a safe, controllable and observable environment. Although no simulators are exact copies of reality, maritime training simulators are deemed to be good training environments by international bodies such as International Maritime Organization (IMO) [45, 20]. Likewise, the cadets that participate in training are not experienced sailors, and therefore it is hard to generalise all findings on cadets to experienced sailors. However, this may be rectified by at least running a control group, where experienced sailors are subject to the same tests as the cadets and the algorithms.

In the future, autonomous vessels may be required to identify themselves as "robots" by transmitting some kind of identification to other seafarers. In this paper, we suggest that testing should be done also without mentioned identification. This is motivated by an assumption that in a mixed environment with regular and autonomous vessels, the traffic will flow safer and more efficiently if the autonomous vessels behave like regular vessels. We believe the proposed experiments will help shed light on this research question as well.

All in all, we argue that test setups such as those described above will be able to provide valuable answers to research questions that are hard, if not impossible, to answer otherwise.

## 8. Conclusions

In this article, we have advocated for using maritime simulators to investigate how well algorithms for autonomous vessels perform in general and especially with humans in the loop. We have identified several interesting research questions that may be hard to answer without the use of the mentioned simulators, and we show that these simulators open up numerous possible research setups that may be explored. We have also identified the need for an interface that allows a third party computer to interact with the simulator. The need for test metrics has also been outlined.

Finally, we strongly argue that it is of great importance that the human-machine interaction between autonomous and traditional vessels is investigated in depth in order to prepare for a future where autonomous and traditional vessels will operate side by side.


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