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Research Article

Environment-adaptive automatic ship collision avoidance system

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Article information	Abstract
Received: May 6, 2026 Revision: July 13, 2026 Accepted: August 26, 2026	Maritime collision accidents remain a critical safety concern despite advances in electronic navigation technology, particularly under adverse weather conditions where reduced visibility and heavy seas substantially degrade a vessel's maneuvering capability. Existing automatic collision avoidance systems typically rely on static ship hazard domains and risk indices that do not incorporate environmental variables, leading to insufficient safety margins in realistic open-sea operation. This paper proposes an integrated environment-adaptive automatic ship collision avoidance system built upon three tightly coupled components: an Automatic Collision Risk Assessment System (ACRAS), a Dynamic Ship Hazard Domain (DSHD) model, and a COLREGs-compliant avoidance algorithm based on a reward-penalty cost function. The ACRAS employs a five-stage hierarchical fuzzy inference architecture containing 160 rules across five functional modules, which simultaneously processes meteorological inputs (wind force, wave height, visibility, and day/night condition) and geometric encounter parameters to produce a normalized Dynamic Risk Factor (DRF) and Final Collision Risk (FCR). The DSHD uses the DRF to dynamically expand the vessel safety boundary with the expansion factor α . The avoidance algorithm employs a three-term cost function comprising course deviation, maneuver stability, and COLREGs penalty terms, combined with a Highest Collision-Risk Ship Candidate priority mechanism to handle multi-vessel encounters. Simulation results demonstrate that the system avoids all five target vessels with a peak rudder deflection of $\pm 23.8^\circ$ while complying with COLREGs Rules 13, 14, 15, 17, and 8, and adapts autonomously to adverse weather without parameter adjustment. The proposed framework provides a computationally efficient and COLREGs-compliant solution for autonomous ship collision avoidance in variable environments.
Keywords Automatic collision avoidance maneuvering; Automatic collision avoidance; Automatic collision risk assessment system; COLREGs compliance; Dynamic ship domain	

1. Introduction

Maritime navigation safety remains one of the most pressing challenges in the global shipping industry. With more than 90 % of world trade carried by sea and continuous growth in vessel traffic density along major shipping routes, the risk of collision accidents poses persistent threats to human life, cargo, and the marine environment. Studies on maritime casualties consistently identify human error as the dominant causative factor. Adverse environmental conditions, including reduced visibility, high sea states, and strong winds, substantially diminish a mariner's situational awareness

and a vessel's maneuvering capability, making such conditions a major aggravating factor in many accidents. Against this background, the development of automatic collision avoidance systems capable of operating in compliance with the International Regulations for Preventing Collisions at Sea (COLREGs) has become an active and strategically important area of maritime research. Research in automatic ship collision avoidance spans two interconnected areas: collision risk (CR) assessment and avoidance maneuvering.

In general, CR assessment is conducted by means of two main approaches: the statistical (data-driven) approach and the computational (analytical/kinematic) approach. Regardless of the approach, most studies have one of two main goals, that is, to construct a Ship Hazard Domain (SHD) model that visually shows the safe operating area of a vessel, or to develop an automated CR assessment system that can quantify the level of risk. Both of these goals aim to produce a CR assessment system with high flexibility and accuracy and which is less dependent on the subjective judgment of mariners.

Statistical/big-data-driven approaches typically draw on historical maritime datasets, most notably those derived from Automatic Identification System (AIS) and Radar records, probabilistic models, and Machine Learning algorithms to find traffic patterns, cluster vessel trajectories, or mariners (experts/officers) perceive risk. The SHDs in this group are called the Empirical Ship Domain (Fiskin, 2023). Pioneering research in this field frequently relied on radar data: Fujii and Tanaka (1971) pioneered the construction of an elliptical SHD for restricted waters; Goodwin (1975) proposed a ship domain containing three disparate segments with constant radii; Davis et al. (1980) and Coldwell (1983) also used Radar data of narrow waters to simulate and construct SHDs. Driven by the widespread adoption of AIS systems in commercial shipping, recent studies have increasingly turned to AIS data to construct SHDs. The study of Rawson et al. (2014) analyzed AIS data to set up an SHD on the Thames river. The studies of Zhou et al. (2022), Silveira et al. (2022), and Kundakci et al. (2023) in recent years continued in the direction of refining SHD models from AIS data. Recent advancements in computational power have significantly streamlined the processing of large-scale datasets, catalyzing a surge in research focused on big data mining and clustering: Zhang et al. (2021) combined K-means and Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithms to cluster vessel trajectories from AIS data in order to assess risk under hydro-meteorological conditions; Liu et al. (2023) used a Kinematics Feature-based Vessel Conflict Ranking Operator (KF-VCRO) based on AIS to identify risk in a continuous manner. Furthermore, machine learning methodologies have gained significant traction in recent years, emerging as a cornerstone of contemporary data-driven research. The study of Zhang et al. (2020) used a Convolutional Neural Network (CNN) to classify levels of risk through images of traffic scenarios; the Bayesian Networks (BN) and Fault Tree Analysis (FTA) models of Ugurlu and Cicek (2022) and Aydin et al. (2021) are very useful for understanding where reinforced risk control measures are possible and worthwhile to reduce the risk of collision in a particular sea area. Nonetheless, the limitations of statistical approaches persist, as their reliance on empirical data often presents inherent complexities that are difficult to circumvent. Consequently, the accuracy of the outcomes is highly contingent upon data integrity; any deficiencies in data completeness, quality, or the rigor of the filtering process can compromise the reliability of the findings. In practice, the loss of AIS signal happens quite frequently due to environmental, as well as human, factors (Liu et al., 2023). The second limitation of this approach is that the data used is limited within a certain time period; therefore, the data may become outdated and need to be updated when there are changes in geography, environmental conditions, or vessel density in the area (Dinh & Im, 2017; Fiskin, 2023). Moreover, machine learning models have low transparency, and it is difficult to explain their results based on COLREGs. At the same time, hydro-meteorological parameters are predominantly neglected, and many AIS-based models only use geometric distance and velocity but ignore the impact of degraded maneuverability due to wind, waves, and currents.

The computational approach to CR assessment offers superior generalizability, as its

application is independent of the specific geographic region from which the data was originally sourced. This approach mainly uses algorithms, spatial geometry, ship dynamics, and control theory to quantify risk. The SHDs constructed by this approach are called the Analytical Ship Domain, defined by mathematical equations, while the CR assessment systems are formed from complex calculation formulas. The early analytical work by Mitrofanov (1968) applied Closest Point of Approach (CPA) and Time to CPA (TCPA) parameters, and Hasegawa and Kouzuki (1987) subsequently introduced fuzzy logic with Time to Closest Point of Approach (TCPA) and Distance to Closest Point of Approach (DCPA) as inputs to produce quantified CR levels. Yoo and Lee (2019) proposed a risk assessment model by directly shifting the SHD to the CPA position to assess risk instead of placing it at the current position. SHD models underpinned by analytical methodologies or fuzzy set theory have garnered significant scholarly interest within the maritime research community. The studies carried out by Wang et al. (2009) and Wang (2013) are pioneering studies in developing SHDs by an analytical framework. Proponents of the computational approach contend that SHDs developed from statistical methods or based on a navigator's experience are typically unrealistic and rather illustrative; in contrast, analytical frameworks facilitate a more systematic and computationally efficient derivation. Other studies of interest include: Pietrzykowski (2008) and Pietrzykowski and Uriasz (2009) built SHDs (Fuzzy Domain) using flexible fuzzy theory; Fiskin et al. (2023) combined Fuzzy Logic with the Analytic Hierarchy Process algorithm to set up an asymmetric polygonal domain; Im and Luong (2019) used a Gaussian kernel density function to create a Potential Risk Ship Domain (PRSD) to assess risk continuously from 0 to 1 at every point around the ship; Zheng et al. (2020) proposed an algorithm to calculate risk based on Support Vector Machine (SVM), considering SHDs as training data to solve the optimization problem of finding the margin between two SHDs, combined with momentum to calculate the consequences of collision. The limitations of the computational approach stem from its overly static and linear assumptions. Specifically, classical parameters such as DCPA and TCPA commonly assuming that the targets keep constant velocity and constant heading, which exposes a notable blind spot when the target ship (TS) suddenly changes its heading (Murray & Perera, 2021). The DCPA and TCPA parameters consider the ship as a point mass and ignore the maneuverability of the ship, as well as environmental conditions. A major limitation of the spatial computational method for building SHDs is that it only warns of the risk without knowing whether the ship has the capacity to maneuver to avoid it. If studies using this method do not take into account the dynamic limits of the ship, the system may give a warning too late, making the avoidance action meaningless. Studies using a pure analytical framework rarely reflect the practical experience of mariners well, which makes the warning boundary become rigid.

Once CR is quantified, the focus shifts to the formulation and execution of optimal avoidance maneuvers. In order to come up with a suitable avoidance maneuvering action, modern studies focus on two main approaches: the heuristic algorithm approach and the deterministic/computational approach.

For the approach using Heuristic/Soft-computing algorithms, studies frequently achieve advantages in solving complex problems in large search spaces. The aim of these studies is not to find an absolutely perfect solution but to find a near-optimal solution within the shortest time. Smierzchalski and Michalewicz (2000) introduced an evolutionary algorithm representing TSs as moving hexagonal hazard zones, optimizing avoidance trajectories for both safety and economy using speed mutation operators, although COLREGs compliance was not explicitly integrated. Zeng (2003) developed a Genetic Algorithm encoding position, speed, and environmental noise in a novel gene structure, balancing safety cost (collision probability) against economic cost (path length, energy consumption), validated aboard the vessel "Shioji Maru," though the convergence time constraint limits real-time applicability. Blach et al. (2012) implemented an A* search with T-neighborhood connectivity, constraining path expansion to dynamically feasible maneuvers within an asymmetric three-zone SHD for COLREGs-compliant inland navigation. Recently, Deep Reinforcement Learning (DRL) has emerged as a dominant trend due to its ability to self-learn through trial and error

and to continuously interact with the environment. Sawada et al. (2021) designed a DRL network using long short-term memory (LSTM) cells in a continuous action space, allowing the ship to give smooth rudder commands instead of discrete heading turns. Chun et al. (2021) applied the proximal policy optimization algorithm combined with a multi-objective reward function, allowing the establishment of flexible avoidance modes such as Safety mode or Efficiency mode. To solve the problem of collision avoidance with multiple TSs in a more sophisticated way, Jiang et al. (2022) proposed an attention-based DRL method that simulates the way mariners distribute their attention to the most dangerous TSs, thereby producing decisions similar to humans. While heuristic and soft-computing approaches offer remarkable adaptability in managing unforeseen collision avoidance scenarios, their practical implementation is often constrained by protracted convergence times and substantial computational overhead (Chun et al., 2021). More importantly, validating deterministic stability and ensuring adherence to COLREGs across the full spectrum of real-world encounters remains a formidable challenge.

For the approach using computational methods, this group of methods uses mathematical models, geometry, ship dynamics, and ship control theory to find an optimal and accurate solution. Several studies have shown impressive results from using Velocity Obstacle (VO), which solves the problem by identifying the sets of velocities that may lead to collision and, from there, choosing a safe velocity vector. Kuwata et al. (2014) successfully applied VO integrated with the COLREGs rules for safe navigation. To overcome the omission of the dynamic characteristics of a ship, Huang and Van Gelder (2020) proposed the Generalized VO algorithm by directly embedding the kinematic constraints of the ship into the control space. Recent advances have concentrated on Artificial Potential Field (APF) variants and hybrid methods. This method creates a virtual force field, in which the goal point creates an attractive force and obstacles create repulsive forces. Lyu and Yin (2019) improved APF by adding conditional virtual forces to force the ship to comply with COLREGs rules in real time. Liu et al. (2023) addressed the limitation of local minima in APF together with improved COLREGs compliance. Recently, He et al. (2023) combined the Model Predictive Control strategy with APF into a Model Predictive Artificial Potential Field, transforming the path planning problem into a non-linear optimization problem to handle complex multi-vessel traffic situations. The study of Dinh and Im (2017) is a hybrid step. The applied method is a combination of statistical and analytical methods to build the SHD, and then the deterministic method is used to come up with the final avoidance action. The Consecutive Waypoints Generation (CWPG) algorithm operates on a set of pre-programmed algorithm rules (complexity rules) to comply with COLREGs, integrated directly with the proportional-integral-derivative (PID) controller of the ship. Limitations of the computational approach: although it is possible to produce accurate ship collision avoidance trajectories, these methods characteristically require huge computational cost when expanding the search space, especially in multi-vessel scenarios; for example, grid-based algorithms, such as Lee's algorithm (Lee, 1961), take too much running time. Studies using the APF method may be stuck in local minima, which is the most characteristic blind spot of the APF method. Chen et al. (2021) points out that when the own ship (OS), the goal, and an obstacle are on the same line, or when an obstacle blocks the heading, the attractive and repulsive forces may cancel each other out, making the algorithm fall into a local minimum, and the ship gets stuck and cannot find the way to the goal. Some path planning algorithms in the studies of Lazarowska (2015, 2017) and Szlapczynski (2015) are based on idealized assumptions; for example, that all TSs always keep constant heading and speed, or always behave according to COLREGs in a standard manner, which is not true when a ship sails in real conditions.

To bridge these gaps, this paper proposes a novel, integrated environment-adaptive automatic ship collision avoidance system. By tightly coupling risk assessment, domain scaling, and avoidance planning, the proposed framework ensures transparent, auditable, and dynamically feasible decisions. The core contributions of this study are threefold:

- (i) Automatic Collision Risk Assessment System (ACRAS): A hierarchical multi-stage

fuzzy inference engine is developed to simultaneously quantify hydro-meteorological risk and geometric encounter risk, synthesizing them into a unified Fuzzy Collision Risk (FCR) index. By utilizing a cascaded decomposition architecture, the system effectively reduces the rule base from a computationally prohibitive 28,000 rules to just 160 transparent rules distributed across five modules, each individually verifiable by maritime experts.

(ii) Dynamic Ship Hazard Domain (DSHD): A dynamic expansion mechanism is introduced wherein the Dynamic Risk Factor (DRF), derived from the ACRAS, parameterizes a multiplicative expansion coefficient (α). This directly couples environmental awareness into the geometry of SHD, automatically enlarging the spatial safety margins under adverse conditions without requiring manual parameter re-tuning.

(iii) Interpretable and COLREGs-Compliant Avoidance Maneuvering: A deterministic optimal heading search algorithm is designed to evaluate candidate trajectories using a three-term cost function. Instead of hard constraints, COLREGs Rules 13, 14, 15, and 17 are encoded as continuous soft-penalties, yielding transparent and auditable decisions that maintain real-time execution without iterative convergence requirements. Additionally, a Highest Collision-Risk Ship Candidate (HCRSC) priority mechanism is implemented to efficiently serialize and resolve complex, overlapping multi-vessel threats.

It can be seen that most of the previous SHD models are only based on static geometric boundaries or kinematic indicators (DCPA, TCPA) and ignore the degradation of the maneuvering capacity of the ship under bad weather conditions (waves, wind, poor visibility). The proposed SHD model can completely overcome this problem with the reshaping of SHD under different environmental conditions. Concerning the CR assessment systems, the limitations of heuristic algorithms are that they take too much time to converge, so it is difficult to meet real-time requirements, while DRL has a “black box” nature, and it is difficult to verify the quality of training data. The ACRAS proposed in this study has a breakthrough point that is its hierarchical multi-stage architecture, which helps to break down the problem. Consequently, the system not only processes extremely quickly in real time but also has transparency and can be verified. With the automatic collision avoidance maneuvering system, it can be seen that the limitations of the APF methods, or the embedding of COLREGs rules into the system as hard constraints, make the algorithms limit the search space, leading to inflexibility or failure in multi-vessel scenarios. The computational methods (such as APF) are frequently stuck in local minima; moreover, embedding COLREGs rules into the system as hard constraints causes the algorithms to be limited in search space, leading to inflexible or failed avoidance actions in multi-vessel scenarios. In this study, the novel system's deterministic optimal heading search algorithm utilizes a three-term cost function comprising course deviation, maneuver stability, and COLREGs penalty. Notably, the COLREGs rules (Rules 13, 14, 15, and 17) are encoded as continuous soft-penalties rather than hard constraints. This allows the system to generate smooth, non-oscillatory decisions and always find a feasible trajectory. In addition, the proposed framework is a tightly coupled closed-loop system that links all three components: Environmental risk assessment (ACRAS) → Safety domain scaling (DSHD) → Avoidance planning. DRF is not merely used for alerts; it directly participates in expanding the DSHD, and this dynamically scaled DSHD subsequently creates spatial constraints for the heading search algorithm. Through this systemic interconnectivity, the vessel's overall operational dynamics dynamically adapt to the evolving environment.

2. Materials and methods

Based on the theoretical framework analyzed above, this study proposes an integrated system comprising three principal modules: ACRAS, DSHD model, and automatic collision avoidance maneuvering.

2.1 Automatic collision risk assessment system

The principal novel contribution of this study is the ACRAS: a hierarchical multi-stage fuzzy

inference engine that simultaneously quantifies hydro-meteorological risk and geometric encounter risk, synthesizing them into a unified FCR index. The FCR index serves a dual purpose: triggering and prioritizing the collision avoidance algorithm; and DRF (a part of the result in the FCR calculation process) parameterizing the expansion coefficient α of the DSHD model, thereby coupling environmental awareness directly into the geometry of the safety zone. The hierarchical architecture is adopted for three reasons. First, a monolithic fuzzy system incorporating all six input variables would require up to 15,625 rules; such an unmanageable rule base cannot be validated against expert knowledge. The cascaded decomposition reduces this to 160 rules distributed across five inference modules, each individually verifiable by maritime domain experts. Second, the staged architecture preserves the physical causal structure of maritime risk: meteorological conditions evolve independently of vessel kinematics, and their effect on CR is mediated through the degradation of vessel controllability and crew situational awareness. Third, each intermediate output carries a physically interpretable meaning (e.g., Weather Forecast, Meteorological Conditions), facilitating system auditing and regulatory acceptance, which is a requirement for safety-critical onboard systems.

2.1.1 System architecture

The ACRAS comprises two parallel processing chains converging at a final synthesis stage, as illustrated in **Figure 1**. All inference modules employ the Mamdani method with min-max composition and centroid defuzzification.

Chain A: Environmental Risk Assessment processes hydro-meteorological inputs through three cascaded stages to produce the DRF, which directly drives the DSHD expansion. Stage 1 (Weather Forecast) fuses wind speed (5 terms, 0 - 100 kn, calibrated to the Beaufort Scale) and sea state (7 terms, 0 - 14 m, aligned with the Douglas Sea Scale) via 35 rules to produce a Weather Forecast (WF) index. Stage 2 (Meteorological Conditions) integrates WF with visibility (5 terms, 0 - 10+ Nautical Miles (NM), calibrated to International Maritime Organization (IMO) categories) through 25 rules to produce the Meteorological Conditions (MC) index; visibility is assigned disproportionately high influence, reflecting the navigational hazard of restricted visibility. Stage 3 (Dynamic Risk Factor) incorporates the day/night cycle (4 temporal terms: Night, Dawn, Day, Dusk) through 20 rules to produce the DRF on a [0, 10] scale.

Chain B: Geometric CR comprises a single fuzzy stage evaluating the relative kinematics of vessel encounters. Stage 4 (CR) processes TCPA and DCPA, normalized to [-1, 1] with five DCPA terms and eight TCPA terms, through 40 rules, to produce a CR index classified on an eight-level scale (Very Safe Positive, Safe Positive, Medium Positive, Dangerous Positive, Very Dangerous Positive, Dangerous Negative, Medium Negative, Safe Negative) (Dinh & Im, 2017; Hasegawa & Kouzuki, 1987). The eight-level taxonomy provides the granularity required by the convergence stage to encode the distinction between developing (positive suffix) and resolving (negative suffix) encounters, which is operationally critical for determining whether evasive action remains warranted. Stage 5 (FCR) synthesizes DRF (5 levels) and CR (8 levels) through 40 rules governed by three design principles: (i) environmental amplification: adverse environmental conditions elevate FCR relative to the geometric baseline; (ii) critical risk invariance: a maximum geometric risk ($CR = VDP$) is never downgraded regardless of environmental context, ensuring that an imminent collision threat is not underestimated in favorable weather; and (iii) favorable condition mitigation: under benign conditions, diverging encounters (negative CR) may be partially downgraded, reflecting the navigator's enhanced situational awareness in calm daylight.

2.1.2 Adaptability to different vessel types

A significant practical advantage of the ACRAS is its adaptability to diverse vessel classes. The core rule bases encode universal maritime risk principles, Beaufort Scale severity thresholds, and IMO visibility categories that are independent of vessel class. Vessel specific characteristics (size, maneuverability index, operational area traffic density) influence only the boundary conditions of the

membership functions: the critical wind speed at which rudder effectiveness begins to degrade, the wave height threshold beyond which autopilot authority should be limited, and the TCPA and DCPA thresholds commensurate with the vessel's stopping distance. These parameters can be re-calibrated for a specific vessel class through expert elicitation or maneuvering trial data without modifying the structural rule bases. This property makes the ACRAS directly extensible from the tanker modeled in this study to coastal vessels, Ro-Ro ferries, or passenger ships with minimal re-engineering effort, positioning the framework for broad operational deployment.

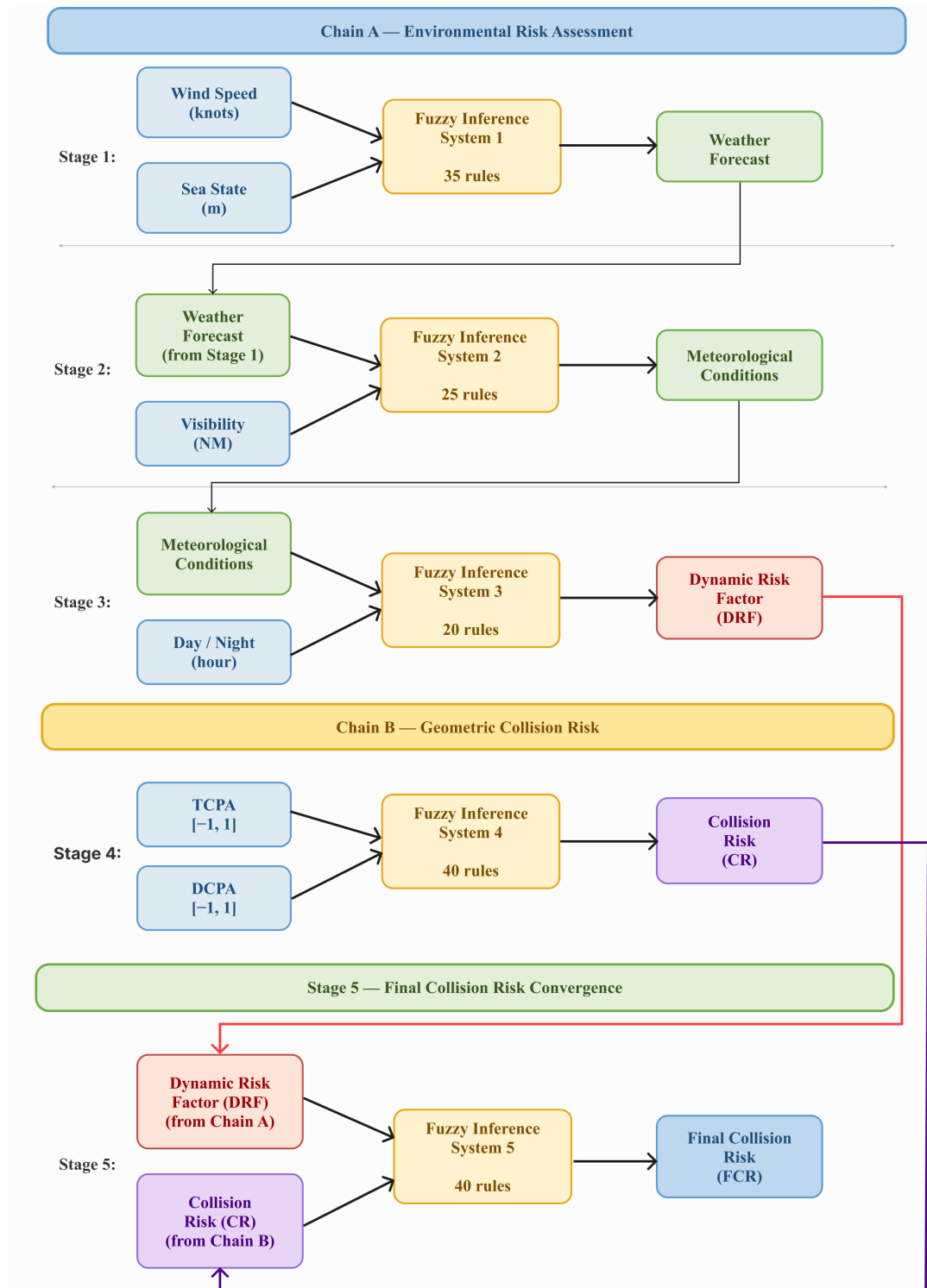


Figure 1 Inference modules of ACRAS.

2.1.3 Membership function design and rule base

All membership functions in the ACRAS take triangular or trapezoidal forms, and none of them was tuned from a proprietary dataset. Their boundary parameters were instead derived from internationally recognized maritime scales combined with expert elicitation: the wind speed terms follow the Beaufort scale, the sea state terms follow the Douglas Sea Scale, and the visibility terms reflect the IMO restricted-visibility categories. The day/night terms trace the natural illumination cycle, while the intermediate and output variables encode established navigational practice. Adjacent functions are arranged to overlap so that every value of each input activates at least one term, which keeps the inference output continuous and avoids abrupt transitions at category boundaries. **Table 1** lists the complete parameters of every input and output linguistic variable.

The full rule base contains 160 rules distributed over the five inference stages, namely, 35 rules for the Weather Forecast, 25 for the Meteorological Conditions, 20 for the Dynamic Risk Factor, 40 for the geometric Collision Risk, and 40 for the Final Collision Risk. Each stage, therefore, remains small enough to be audited line by line. All stages employ Mamdani inference with min-max composition and centroid defuzzification, and the synthesis stage follows the three design principles stated in Section 2.1.1. **Table 2** presents representative rules from each stage together with their navigational rationale; the complete rule tables are available from the authors upon request.

Table 1 Membership function parameters of the ACRAS linguistic variables (triangular: (a, b, c); trapezoidal: (a, b, c, d)).

Linguistic variable (universe)	Membership functions: type (parameters)	Design basis
Wind speed (0 - 100 kn)	Light: tri (0, 0, 20); Moderate: tri (4, 25, 46); Strong: tri (29, 50, 71); Very Strong: tri (54, 75, 96); Very Dangerous: tri (79, 100, 100)	Beaufort scale
Sea state (0 - 14 m)	Calm: trap (0, 0, 0.1, 0.5); Slight: trap (0.1, 0.5, 1, 1.25); Moderate: trap (1, 2, 2.5, 3); Rough: trap (2.5, 4, 4.5, 5.5); Very Rough: trap (5, 6.5, 7, 8); High: trap (7.5, 9, 9.5, 10.5); Very High: trap (10, 12, 14, 14)	Douglas Sea Scale
Weather Forecast, WF (0 - 10)	Very Good: trap (0, 0, 1, 2); Good: tri (1, 2.5, 4); Moderate: tri (3, 5, 7); Poor: tri (6, 7.5, 9); Very Poor: tri (8, 10, 10)	Intermediate output of Stage 1
Visibility (0 - 10+ NM)	Very Poor: trap (0, 0, 0.5, 1); Poor: tri (0.5, 1, 2); Moderate: tri (1.5, 3, 5); Good: tri (4, 6, 8); Very Good: trap (7, 9, 10, 10)	IMO visibility categories
Day/Night (0 - 24 h)	Night: trap (0, 0, 4, 6) and trap (18, 20, 24, 24); Dawn: trap (4, 6, 7, 8); Day: trap (7, 9, 15, 17); Dusk: trap (16, 17, 18, 20)	Natural illumination cycle
Meteorological Conditions, MC (0 - 10)	Very Dangerous: trap (0, 0, 1, 2); Dangerous: tri (1, 2.5, 4); Moderate: tri (3, 5, 7); Safe: tri (6, 7.5, 9); Very Safe: tri (8, 10, 10)	Intermediate output of Stage 2
Dynamic Risk Factor, DRF (0 - 10)	Very Low Risk: tri (0, 0, 2); Low Risk: tri (1, 2.5, 4); Moderate Risk: tri (3, 5, 7); High Risk: tri (6, 7.5, 9); Very High Risk: tri (8, 10, 10)	Output of Stage 3

Note: tri and trap denote triangular and trapezoidal membership functions; all parameters correspond to the fuzzy inference systems implemented in MATLAB/Simulink. The DCPA input of Stage 4 uses five terms and the TCPA input uses eight terms, both normalized to $[-1, 1]$ following (Dinh & Im, 2017; Hasegawa & Kouzuki, 1987); the CR output uses the eight-level taxonomy described in Section 2.1.1.

Table 2 Representative fuzzy rules of the five inference stages (two representative rules per stage).

Inference stage	Representative rule	Navigational rationale
Stage 1: Weather Forecast (35 rules)	IF Wind Speed is Light AND Sea State is Calm THEN WF is Very Good	Benign weather yields the lowest environmental severity
	IF Wind Speed is Very Dangerous AND Sea State is Rough THEN WF is Very Poor	Extreme wind dominates the assessment regardless of sea state
Stage 2: Meteorological Conditions (25 rules)	IF WF is Very Poor AND Visibility is Very Poor THEN MC is Very Dangerous	Restricted visibility carries a deliberately high weight
	IF WF is Very Good AND Visibility is Very Poor THEN MC is Dangerous	Fog governs the assessment even in calm weather
Stage 3: Dynamic Risk Factor (20 rules)	IF MC is Very Dangerous AND Day/Night is Night THEN DRF is Very High Risk	Darkness amplifies the meteorological hazard
	IF MC is Very Safe AND Day/Night is Day THEN DRF is Very Low Risk	Favorable conditions restore the baseline domain
Stage 4: Collision Risk (40 rules)	IF DCPA is Dangerous Positive AND TCPA is Dangerous Positive THEN CR is Very Dangerous Positive	A close, imminent, and still developing encounter
	IF DCPA is Safe Positive AND TCPA is Very Safe Positive THEN CR is Very Safe Positive	A wide passing distance with ample time remaining
Stage 5: Final Collision Risk (40 rules)	IF DRF is Very High Risk AND CR is Medium Negative THEN FCR is Very Dangerous Positive	Environmental amplification of a mild geometric risk
	IF CR is Very Dangerous Positive THEN FCR is Very Dangerous Positive, for any DRF	Critical-risk invariance; an imminent threat is never downgraded

2.2. Dynamic ship hazard domain model

2.2.1. Baseline SHD model

The DSHD model proposed in this study is built upon the baseline SHD developed by Dinh and Im (2017), extended through an environment-adaptive expansion mechanism governed by real time hydro-meteorological conditions. As illustrated in **Figure 2**, the baseline SHD comprises two functional zones: (i) the Blocking Area (BLA): a polygonal zone of absolute prohibition whose boundaries are determined by vessel maneuvering parameters and (ii) the Action Area (ATA): a circular zone specifying the distance at which evasive maneuvering must be initiated, calibrated empirically through surveys of 60 experienced maritime officers (Dinh & Im, 2016, 2017).

The BLA forward, aft, port, and starboard dimensions (D_f , D_a , D_p , D_s) are formulated per COLREGs encounter type.

For *head-on encounters* (Rule 14 of the COLREGs), the BLA is defined by Eq. (1):

$$\begin{cases} D_f = Adv_o + Adv_t + ErrGPS + \Delta \\ \quad = Adv_o - 0.0028513L_t^2 + 4.2668L_t + 78.6414 \\ D_s = D_p = D_a = MinPD + ErrGPS \\ \quad = 3.4961L_t + 50.576 \end{cases} \quad (1)$$

Where,

D_f Forward dimension of BLA; minimum safe distance required ahead of TS to allow emergency turning maneuvers

- D_a Aft dimension of BLA; minimum safe distance astern of TS
 D_p Port-side dimension of BLA; minimum safe distance on the port side of TS
 D_s Starboard-side dimension of BLA; minimum safe distance on the starboard side of TS
 Adv_t Advance distance of the turning circle of TS; determined by linear regression from maneuvering trial data of 100 commercial vessels
 Adv_o Advance distance of the turning circle of OS
 L_t Length of TS; independent variable in the regression equation for Adv_t
 B_t Breadth of TS; independent variable in the regression equation for Adv_t
 Δ Maximum regression residual; maximum deviation between predicted and actual advance distance values (≈ 134.16 m)
 $ErrGPS$ Maximum user range error of GPS Standard Positioning Service (SPS) adopted as 25.495 m
 $MinPD$ Minimum safe passing distance; determined statistically from survey of 60 experienced maritime officers

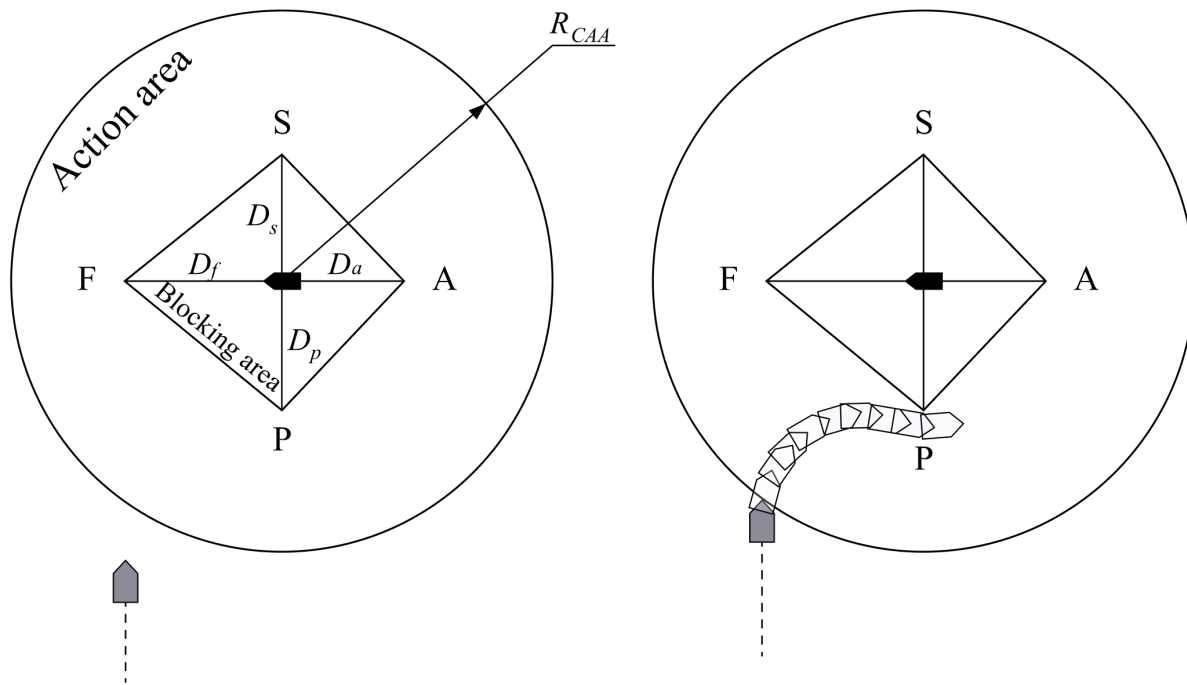


Figure 2 Baseline SHD developed by Dinh and Im (2017).

For *crossing encounters* (Rule 15 of the COLREGs), the BLA is defined by Eq. (2):

$$\left\{ \begin{array}{l} D_f = Adv_t + ErrGPS + \Delta \\ \quad = -0.0028513L_t^2 + 4.2668L_t - 78.6414 \\ D_p = Adv_o + ErrGPS \\ \quad = Adv_o + 25.495 \\ D_s = D_a = MinPD + ErrGPS \\ \quad = 3.4961L_t + 50.576 \end{array} \right. \quad (2)$$

For *overtaking encounters* (Rule 13 of the COLREGs), the BLA is defined by Eq. (3):

$$\begin{cases} D_f = Adv_t + ErrGPS + \Delta \\ \quad = -0.0028513L_t^2 + 4.2668L_t - 78.6414 \\ D_s = D_p = D_a = MinPD + ErrGPS \\ \quad = 3.4961L_t + 50.576 \end{cases} \quad (3)$$

The parametric relationships for Adv_t and $MinPD$ as functions of the vessel's length overall (LOA), established by linear regression on maneuvering data from 100 commercial vessel, are expressed in Eq. (4):

$$Adv_t = -0.0028513L_t^2 + 4.2668L_t - 81.015 \quad (4)$$

In order to determine $MinPD$, the survey is implemented by 60 officers; the conclusion computed is shown below by Eq. (5):

$$MinPD = 7.896B_t + 381.03 \quad (5)$$

The ATA radius is computed in two situations of approach in head-on situation and is expressed in Eq. (6):

$$R_{CAA} = D_f + t'_{Av-H} V_{relative} = D_f + 616.74V_{relative} \quad (6)$$

Where,

- R_{CAA} Radius of ATA; the appropriate action-initiation distance from the approaching TS
- $V_{relative}$ Relative velocity between OS and TS; used to convert action distances to action times
- t'_{Av-H} Adjusted action time for head-on; the time for OS to reach the forward BLA boundary (F) of TS's domain under survey conditions

In crossing situation is expressed in Eq. (7):

$$R_{CAA} = D_p + t'_{Av-C} V_{relative} = D_p + 926.64V_{relative} \quad (7)$$

Where,

- t'_{Av-C} Adjusted action time for crossing; the time for OS to reach the port-side BLA boundary (P) of TS's domain under survey conditions

2.2.2 Dynamic expansion mechanism

The principal contribution of the DSHD model is a multiplicative expansion coefficient α that scales all BLA dimensions in real time according to the prevailing environmental risk level, quantified by the ACRAS fuzzy inference system (Section 2.1) and formulated as follows in Eq. (8):

$$\alpha = 1 + \beta \times DRF_{normalized} \quad (8)$$

Where $DRF_{normalized} \in [0, 1]$ is the normalized DRF output of ACRAS, and β is the maximum expansion weight. The expanded BLA dimensions are updated by Eq. (9):

$$D'_f = D_f \times \alpha; \quad D'_s = D_s \times \alpha; \quad D'_p = D_p \times \alpha; \quad D'_a = D_a \times \alpha \quad (9)$$

Under benign conditions ($DRF_{normalized} \approx 0$, $\alpha \approx \min$), the DSHD reverts to the static baseline, preserving navigational efficiency. Under adverse conditions ($DRF_{normalized} \rightarrow 1$, $\alpha \rightarrow \max$), the domain expands up to α times its baseline dimensions to compensate for degraded rudder effectiveness in heavy seas, increased Global Positioning System (GPS) positioning uncertainty, and reduced radar detection range in low visibility.

It is important to clarify that, while the baseline SHD model incorporates a static positioning error (Err_{GPS} in Eq. (1)) to represent nominal sensor uncertainty under ideal conditions, the dynamic expansion multiplier α inherently acts as a compensatory buffer for weather-induced sensor degradation. In rough seas and adverse meteorological environments, factors such as severe sea clutter, rain attenuation, and intense vessel motions significantly degrade the accuracy of marine radar and introduce tracking latencies or filtering errors in Automatic Radar Plotting Aid (ARPA) algorithms. Rather than explicitly modeling these highly stochastic sensor noises within the kinematic equations, the proposed framework employs the environmental risk factor quantified by the ACRAS to expand the spatial safety boundaries. Consequently, the enlarged BLA parameterized by α implicitly absorbs these elevated sensor uncertainties, ensuring that a reliable safety margin is maintained even when the perceived states of target ships are subject to environmental tracking degradation.

Critically, α is governed exclusively by slowly-evolving environmental variables rather than proximity-based parameters (TCPA, DCPA), ensuring domain stability throughout critical avoidance maneuvers and preventing erratic fluctuations in the collision avoidance algorithm.

2.3 Automatic collision avoidance maneuvering

The collision avoidance module integrates the risk outputs of ACRAS and the DSHD model into a closed loop heading controller that operates in real time. Its per-cycle architecture consists of five sequential modules: multi-sensor data acquisition from radar/ ARPA, AIS, and environmental sensors; DSHD computation using the normalized DRF from ACRAS; conflict detection by forward-projecting own-ship and target-ship trajectories over a prediction horizon; optimal heading search; and autopilot command transmission. This architecture ensures that every heading command is simultaneously safe, COLREGs-compliant, and navigational-efficiency-aware.

2.3.1 Search space and safety constraint

At each decision cycle, the candidate heading set is constructed by discretizing the reachable heading interval. Let $\psi_{current}$ denote the current heading, Θ_{max} the maximum heading deviation admissible within a single cycle, and $\Delta\psi$ the angular search resolution. The discrete search space is defined by Eq. (10):

$$\Omega_{\psi} = \{\psi \mid \psi = \psi_{current} + k \cdot \Delta\psi, \quad k \in \mathbb{Z}, \quad -\frac{\Theta_{max}}{\Delta\psi} \leq k \leq \frac{\Theta_{max}}{\Delta\psi}\} \quad (10)$$

A heading $\psi_i \in \Omega_{\psi}$ is classified as safe if the predicted own-ship position $P_{OS}(\tau \mid \psi_i)$ does not intersect the DSHD of any TS over the forward-looking horizon $T_{predict}$, as formally defined in Eq. (11):

$$C_{safe} = \{\psi_i \in \Omega_{\psi} \mid \forall \tau \in [0, T_{predict}], P_{OS}(\tau \mid \psi_i) \cap DSHD_{TS}(\tau) = \emptyset\} \quad (11)$$

The DSHD boundary is parameterized by the expansion coefficient derived in Eq. (9), ensuring the effective exclusion zone grows automatically in proportion to the prevailing environmental and geometric risk.

2.3.2 Objective function and COLREGs quantification

Each safe candidate heading is evaluated by a three-term weighted cost function that simultaneously penalizes route deviation, command instability, and COLREGs non-compliance, as formulated in Eq. (12):

$$J(\psi_i) = w_1 \cdot C_{dev}(\psi_i) + w_2 \cdot C_{stab}(\psi_i) + w_3 \cdot C_{rule}(\psi_i) \quad (12)$$

The individual components of the cost function are mathematically formulated as follows: the deviation cost $C_{dev}(\psi_i)$, defined by Eq. (13), quantifies the angular departure from the intended route. To ensure smooth navigation, the stability cost $C_{stab}(\psi_i)$, expressed in Eq. (14), penalizes significant inter-cycle heading changes to suppress oscillatory maneuvers. Finally, the rule cost $C_{rule}(\psi_i)$ as formulated in Eq. (15) encodes COLREGs obligations into the system via a vessel-encounter soft-penalty mechanism:

$$C_{dev}(\psi_i) = \frac{|\psi_i - \psi_{dest}|}{\pi} \quad (13)$$

$$C_{stab}(\psi_i) = \frac{|\psi_i - \psi_{prev_cmd}|}{\Theta_{max}} \quad (14)$$

$$C_{rule}(\psi_i) = \sum_{k=1}^M P_{COLREG}(\psi_i, TS_k) \quad (15)$$

where the COLREGs penalty term P_{COLREG} assigns a heavy penalty λ for port side maneuvers in head-on crossing encounters, a light penalty μ for stand-on vessels that unnecessarily deviate to port side (COLREGs Rule 17) for crossing encounters, and zero for fully compliant actions: starboard turn in head-on or crossing encounters (keep out of the way situation), either-side maneuver in overtaking (COLREGs Rule 13), and course-keeping on the stand-on vessel.

2.3.3 Optimal heading selection and rate-limited output

The optimal command heading is selected as the element of C_{safe} that minimizes the aggregate cost, as formulated in Eq. (16):

$$\psi_{opt} = \arg \min_{\psi_i \in S_{safe}} \{J(\psi_i)\} \quad (16)$$

If C_{safe} is empty, indicating that all candidate headings intersect a TS's DSHD, the algorithm enters an emergency mode. It is important to clarify that the system is fundamentally designed as a continuous heading controller to maintain a one-dimensional search space, which guarantees ultra-fast real-time convergence. Integrating speed as a continuous variable within the objective function (Eq. (12)) would exponentially expand the search space into two dimensions, potentially compromising computational efficiency. Therefore, the mathematical mechanism for speed reduction is not formulated within the continuous optimization space, but is instead implemented as a discrete, rule-based emergency override.

During this emergency mode, the algorithm suspends the standard cost function evaluation. It selects the heading that yields the minimum intrusion depth into the obstacle's DSHD and simultaneously issues a step-down command to the vessel's main engine revolution rate. Within the MMG dynamic modeling framework, this sudden reduction in propeller RPM directly decreases the propeller's advanced ratio and the corresponding thrust coefficient, as governed by Eq. (22) in Section 2.4. Consequently, the propeller-induced surge force X_p in Eq. (21) of Section 2.4 drops

significantly, causing the vessel to hydrodynamically decelerate. This deceleration effectively buys time and alters the encounter geometry until a valid, non-intersecting C_{safe} set is re-established in the subsequent decision cycles. Prior to transmission to the autopilot, a rate limiter defined by Eq. (17) enforces mechanical continuity of the rudder command:

$$|\psi_{cmd}(t) - \psi_{cmd}(t-1)| \leq \dot{\psi}_{limit} \cdot \Delta t \quad (17)$$

This rate constraint, combined with the stability term C_{stab} in the cost function (Eq. (14)), produces smooth, seamanlike maneuvers consistent with COLREGs Rule 8. The complete per-cycle decision loop from sensor data acquisition to autopilot rudder command is summarized in **Figure 3**.

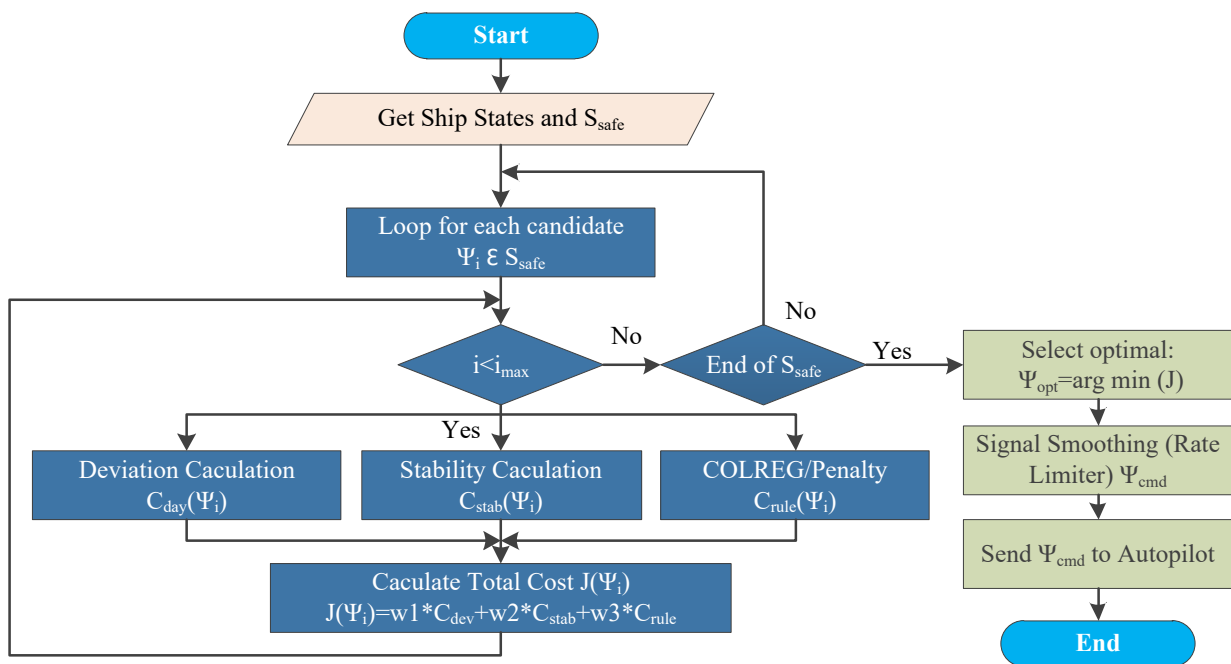


Figure 3 Per-cycle decision loop of the collision avoidance algorithm.

2.4 Ship dynamics modeling (MMG model)

Over the past several decades, numerous mathematical modeling frameworks have been developed to predict ship motion. Among these, the MMG (Mathematical Modeling Group) model has emerged as a widely accepted standard for maneuvering simulation. The MMG model was originally introduced by the Mathematical Modeling Group, established by the Maneuvering Committee of the Japan Towing Tank Conference in March 1976. The three-degree-of-freedom (3-DOF) MMG model consists of three coupled motion equations that describe the forces and moment at the vessel's center of gravity, as expressed in Eq. (18). In this formulation, X and Y represent the external forces acting along the x -axis and y -axis, respectively, while N denotes the yaw moment about the z -axis. These force and moment components are derived from the steady-state hydrodynamic contributions of the hull, propeller, and rudder subsystems. The MMG model implemented in this study simulates the ship dynamics with wind and second-order wave-drift forces entering Eq. (18) as external force terms. Their effect on collision risk is additionally captured through the dynamic expansion of the DSHD, as detailed in Section 2.2.2, a mechanism that sustains computational efficiency while the real-time safety margin is preserved.

$$\begin{cases} (m + m_x)\dot{u} - (m + m_y)vr = X \\ (m + m_y)\dot{v} + (m + m_x)ur = Y \\ (I_{zz} + J_{zz})\dot{r} = N \end{cases} \quad (18)$$

The external forces and moment components acting on the vessel can be decomposed according to Eq. (19):

$$\begin{cases} X = X_H + X_P + X_R \\ Y = Y_H + Y_P + Y_R \\ N = N_H + N_R + N_R \end{cases} \quad (19)$$

The hull forces X_H , Y_H and N_H are expressed through non-dimensional polynomial functions of the drift angle β and non-dimensional yaw rate r . In this study, the following formulation is adopted in Eq. (20):

$$\begin{aligned} X_H &= \frac{\rho}{2} L d U^2 \left(X'_{\beta r} \frac{rL}{U} \sin \beta + X'_{uu} \cos^2 \beta \right) \\ Y_H &= \frac{\rho}{2} L d U^2 \left[Y'_{\beta} \beta + Y'_{\frac{rL}{U}} \frac{rL}{U} + Y'_{\beta\beta} \beta^2 + Y'_{\beta r} \beta \left(\frac{rL}{U} \right) + Y'_{rr} \left(\frac{rL}{U} \right)^2 \right] \\ N_H &= \frac{\rho}{2} L d U^2 \left[N'_{\beta} \beta + N'_{\frac{rL}{U}} \frac{rL}{U} + N'_{\beta\beta} \beta^2 + N'_{\beta r} \beta \left(\frac{rL}{U} \right) + N'_{rr} \left(\frac{rL}{U} \right)^2 \right] \end{aligned} \quad (20)$$

The propeller-induced forces and moment X_P , Y_P and N_P are calculated using Eq. (21):

$$\begin{cases} X_P = (1-t) p K_T D_p^4 n^2 \\ Y_P = 0 \\ N_P = 0 \end{cases} \quad (21)$$

Where K_T , defined in Eq. (22) is the thrust coefficient of the propeller, and J is an advanced constant of the propeller.

$$K_T = a_0 + a_1 J + a_2 J^2 \quad (22)$$

X_R , Y_R and N_R are determined based on interactions between the hull and rudder in Eq. (23):

$$\begin{cases} X_R = -(1-t_R) F_N \sin \delta \\ Y_R = -(1-a_H) F_N \cos \delta \\ N_R = -(x_R + a_H x_H) F_N \cos \delta \end{cases} \quad (23)$$

Where F_N represents the rudder normal force, which is formulated in Eq. (24):

$$F_N = \frac{\rho}{2} A_R f_\alpha U_R^2 \sin \alpha_R \quad (24)$$

In this formulation, δ is the rudder angle, A_R is the rudder area, U_R is the effective inflow velocity to the rudder, and f_α is the rudder lift gradient coefficient.

2.5 Simulation setup

The proposed collision avoidance system was implemented and validated in a MATLAB/Simulink simulation environment. The simulated vessel is the KVLCC2 (KRISO Very Large Crude oil Carrier 2; Korea Research Institute of Ships and Ocean Engineering), a well-established benchmark hull form widely used in ship maneuvering and control research. The key principle dimensions and hydrostatic parameters of the KVLCC2 are summarized in **Table 3**.

Table 3 Principal dimensions of the KVLCC2 benchmark ship model.

Parameter	Value
Ship length (L)	320 m
Beam (B)	58 m
Draft (d)	20.8 m
Displacement (Δ)	312,622 m ³
Design speed (U_0)	15.5 kn (1 kn = 0.514 m/s)
Block coefficient (CB)	0.8098

A PID heading controller was employed as the inner-loop autopilot. The PID gains were tuned to achieve a balance between fast response and adequate damping for the large tanker dynamics, yielding the values: $K_p = 2.814$, $K_i = 0.112$, $K_d = 17.65$. These gains were held constant throughout all simulation scenarios. The complete collision avoidance system was modeled in MATLAB/Simulink as a closed-loop architecture comprising six functional blocks interconnected in a per-cycle execution loop.

The Ship Dynamics block implements the three-degree-of-freedom MMG model, integrating the surge, sway, and yaw equations to propagate the own-ship state given a commanded heading. The CPA Calculator block continuously computes the TCPA and the DCPA for each detected TS. The Risk Assessment block integrates the ACRAS five-stage fuzzy hierarchy and the DSHD module to produce the FCR value and the dynamically scaled hazard domain for each target. Among all detected TSs, the HCRSC selector identifies the vessel posing the greatest threat at each decision cycle and passes it to the Collision Avoidance Algorithm block. The Collision Avoidance Algorithm block executes the per-cycle decision loop, which discretizes the heading search space Ω_ψ , builds the safety set C_{safe} by checking trajectory predictions against DSHD constraints, evaluates the cost function $J(\psi_i)$ for all safe candidates, and outputs the optimal heading ψ_{opt} through the rate limiter. The resulting heading command ψ_{cmd} is fed to the PID Autopilot block, which converts it into rudder angle commands for the Ship Dynamics block.

Two simulation scenarios of increasing complexity were conducted to evaluate the performance of the proposed system. The simulation domain spans 40×25 nautical miles. All scenarios use the KVLCC2 ship model with initial speed $U_0 = 7.9$ kn and maximum rudder angle $\delta_{max} = \pm 35^\circ$.

2.5.1 Scenario 1: Multi-target collision avoidance

Scenario 1 tests the system under a complex multi-target traffic environment. Five TSs (TS1-TS5) are placed within the simulation domain with various headings and speeds, creating a sequence of overlapping collision threats. The OS starts at (−20, 4) NM and must reach (20, 4) NM while

negotiating all encounters. At each decision cycle, the HCRSC selector identifies the highest-priority threat, and the avoidance algorithm computes a COLREGs-compliant maneuver against it.

In this scenario, all TSs are configured to maintain a constant course and speed, thereby acting strictly as stand-on vessels to evaluate the system under the worst-case burden of avoidance compliance. While the targets remain non-evasive here, any potential uncertainty regarding their future trajectories is inherently mitigated by the high-frequency closed-loop architecture of the proposed system. Because the dynamic safety boundaries and optimal headings are recalculated entirely anew at each discrete decision cycle based on real-time sensor updates, any sudden trajectory alterations by target vessels would be immediately captured and resolved by the feedback loop in subsequent cycles.

2.5.2 Scenario 2: Environmental adaptability

Scenario 2 investigates the adaptability of the DSHD mechanism to degraded environmental conditions. The encounter geometry is in single-target crossing but is executed under two weather regimes: normal conditions (good visibility, calm sea state) and adverse conditions (reduced visibility, Beaufort 6 wind, significant wave height $H_s = 2 - 3$ m). The environmental parameters for each regime are summarized in **Table 4**.

Table 4 Environmental parameters for Scenario 2 (normal vs. adverse conditions).

Parameter	Normal Conditions	Adverse Conditions
Visibility	Good (>10 NM)	Reduced (<3 NM)
Wind speed	Beaufort 2 - 3	Beaufort 6
Significant wave height (H_s)	<1 m	2 - 3 m
Domain Multiplier coefficient (α)	≈ 1.0	1.3 - 1.8

3. Results

3.1 Scenario 1: Multi-target collision avoidance

The sequential avoidance trajectory is shown in **Figure 4**. In the initial phase (**Figure 4a**), TS5 is identified as the most dangerous vessel and the OS executes a starboard avoidance maneuver. As TS5 and TS1 are cleared (**Figures 4c - 4d**), the OS begins returning to its original route. A new threat, TS3, is then identified (**Figure 4e**) and a second avoidance maneuver is initiated. After all conflicts are resolved (**Figure 4f**), the OS successfully completes its route. The rudder angle variations throughout the encounter are shown in **Figure 5**, with peak deflections of up to $\pm 23.8^\circ$ during the most demanding avoidance phases.

The results demonstrate that the HCRSC-based priority mechanism correctly sequences the avoidance actions, preventing simultaneous conflicting maneuvers that could arise from attempting to avoid all targets at once. The COLREGs penalty term in the cost function ensures that all maneuvers are executed to the starboard side as prescribed by the applicable collision regulations.

3.2 Scenario 2: Environmental adaptability

Under adverse conditions, the ACRAS environmental sub-system elevates the Domain Multiplier (DM) coefficient - α in Eq. (8) causing the DSHD to expand proportionally. The evolution of α over time and the corresponding DSHD size are shown in **Figures 6** and **7**. In the adverse-weather run, α rises to ≈ 1.36 (measured range 1.06 - 1.36), enlarging the safety domain, so that a larger heading deviation is required to clear it than in the normal weather case.

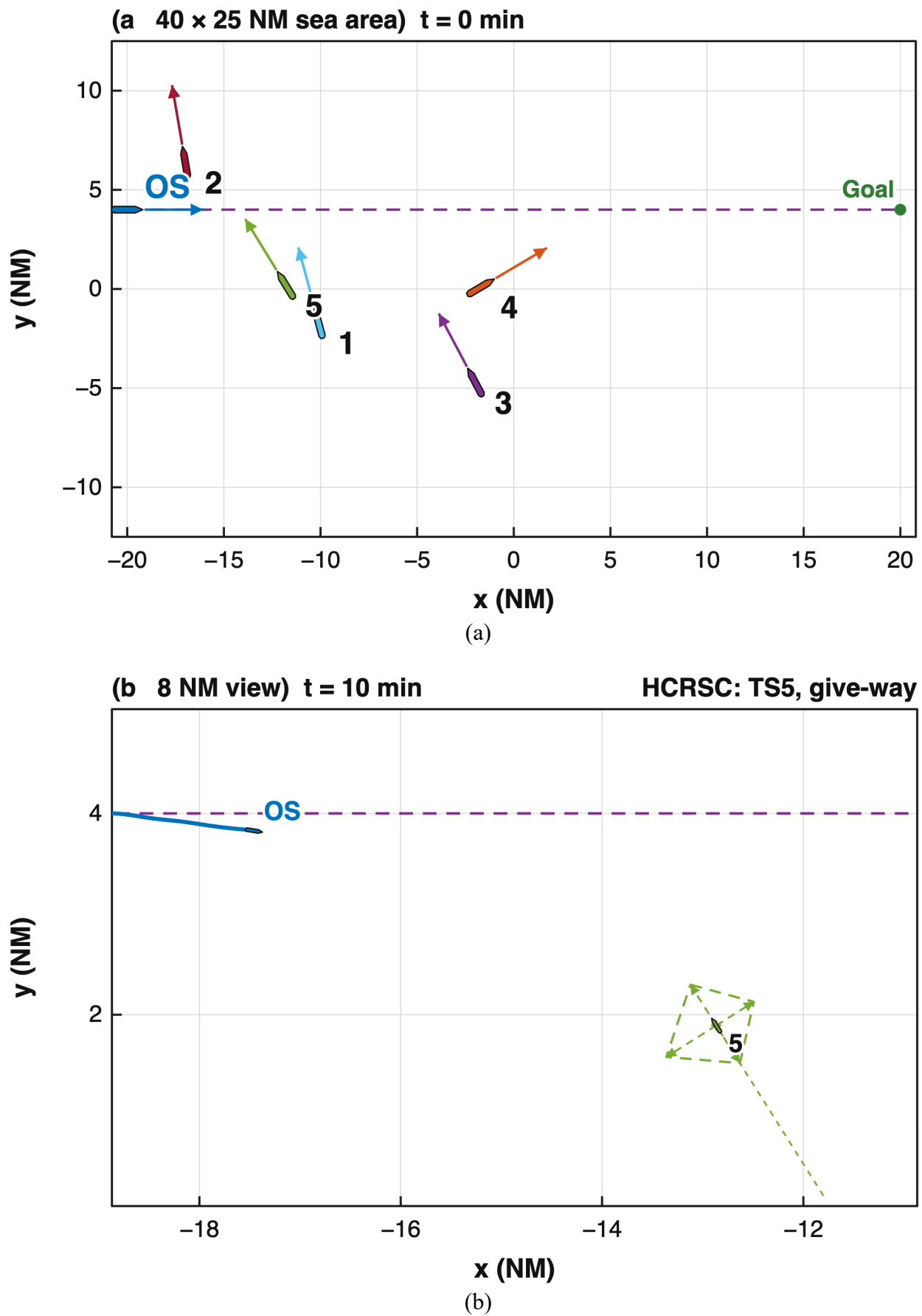


Figure 4 Sequential multi-target avoidance trajectory.

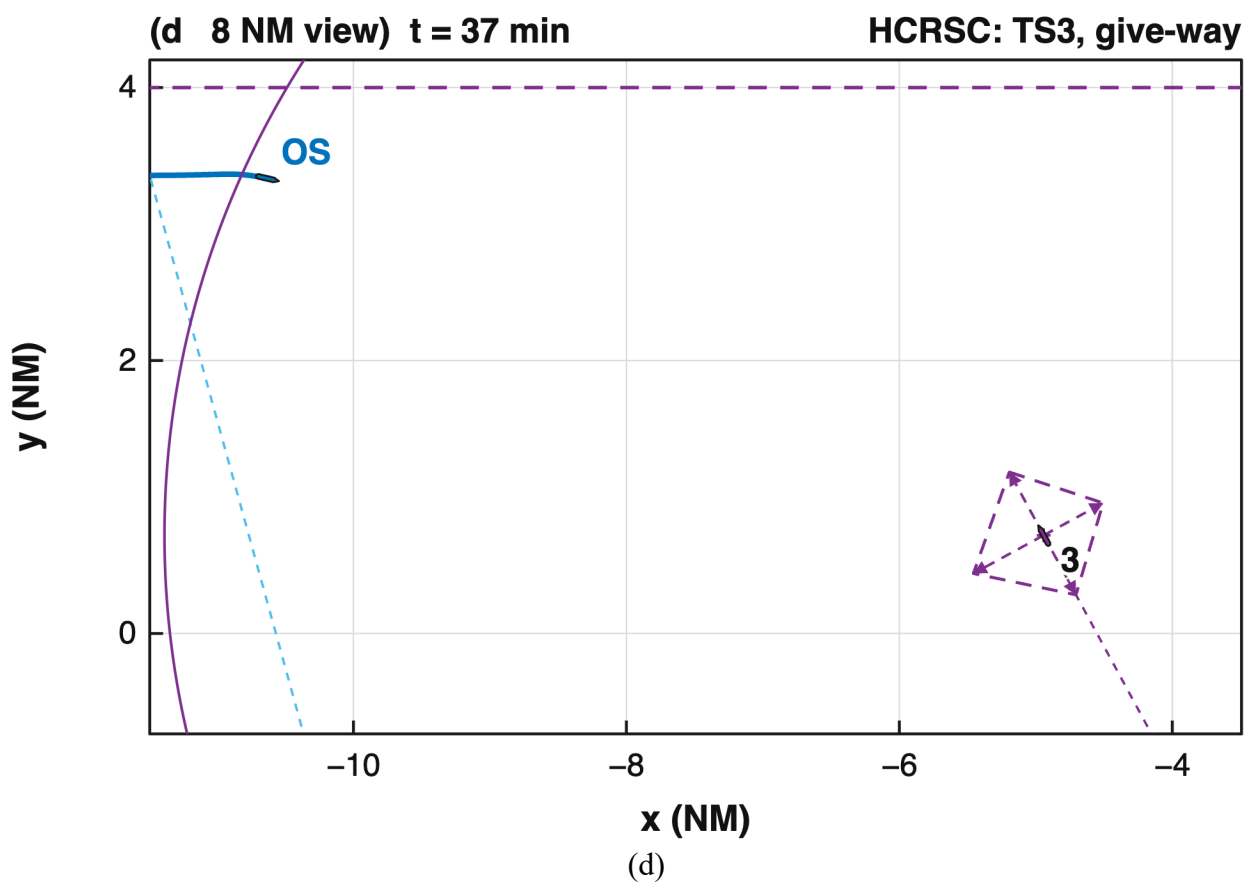
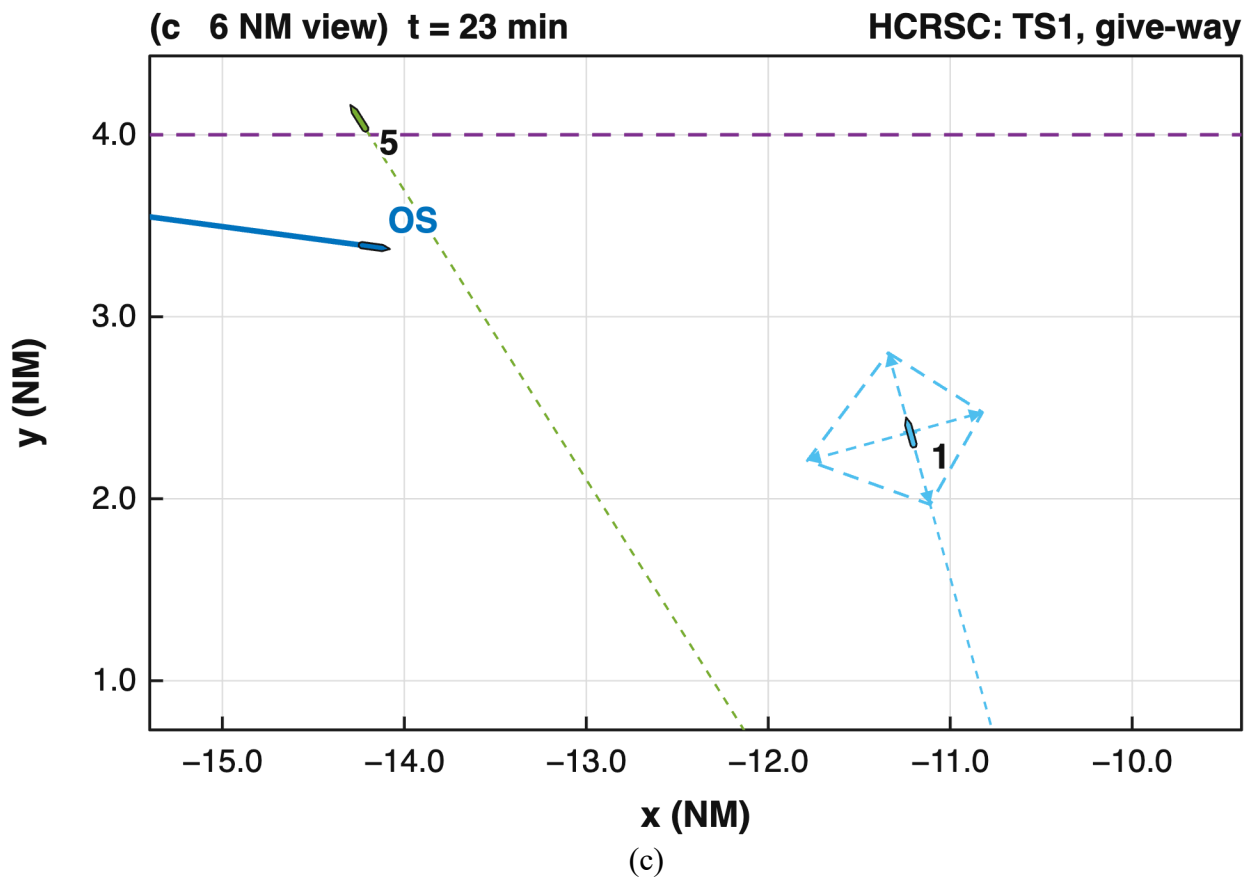


Figure 4 (continued) Sequential multi-target avoidance trajectory.

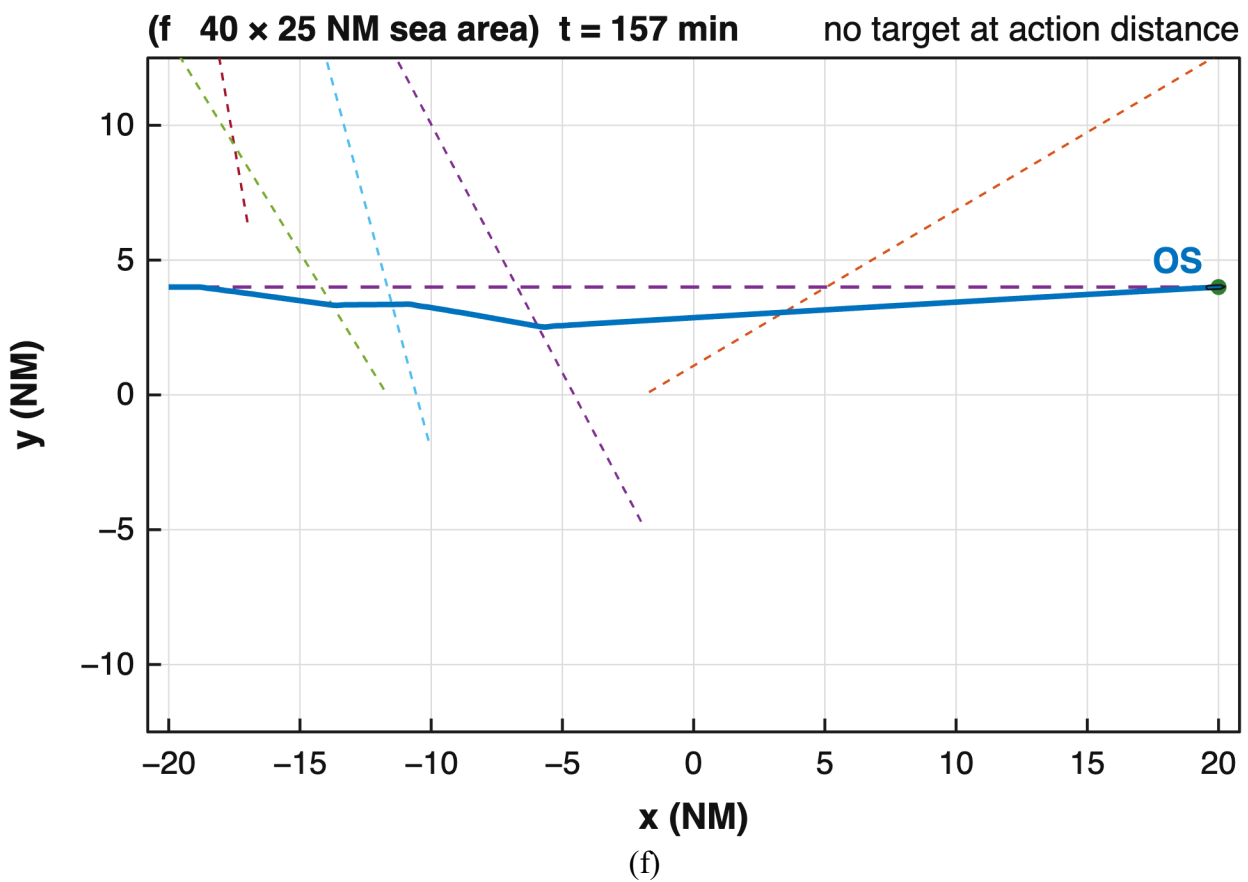
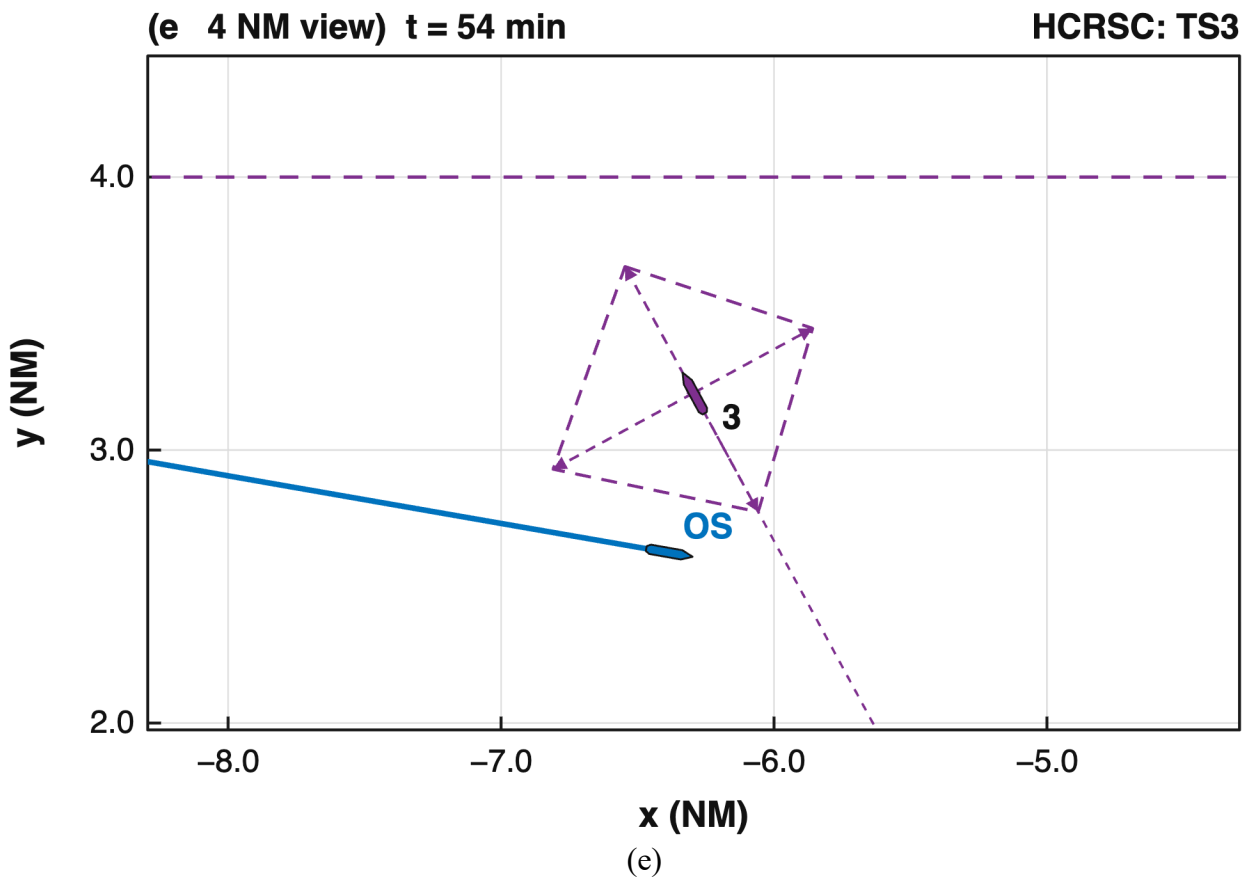


Figure 4 (continued) Sequential multi-target avoidance trajectory.

Figures 8 - 10 present the comparative rudder angle, heading, and trajectory plots for the two weather regimes. Under adverse conditions, the OS executes a larger heading deviation (21.3° against 9.6°) to maintain clearance from the expanded DSHD. Despite the larger maneuver amplitude, the rate limiter (Eq. (17)) ensures that the rudder command remains smooth and within the physical limits of the steering gear.

The Scenario 2 results confirm that the DSHD expansion mechanism provides a meaningful increase in safety margin under degraded conditions without requiring manual re-tuning of the avoidance algorithm. The system inherits environmentally adaptive behavior directly from the ACRAS DRF sub-system, demonstrating the benefit of the tightly coupled risk assessment-domain scaling-avoidance planning architecture.

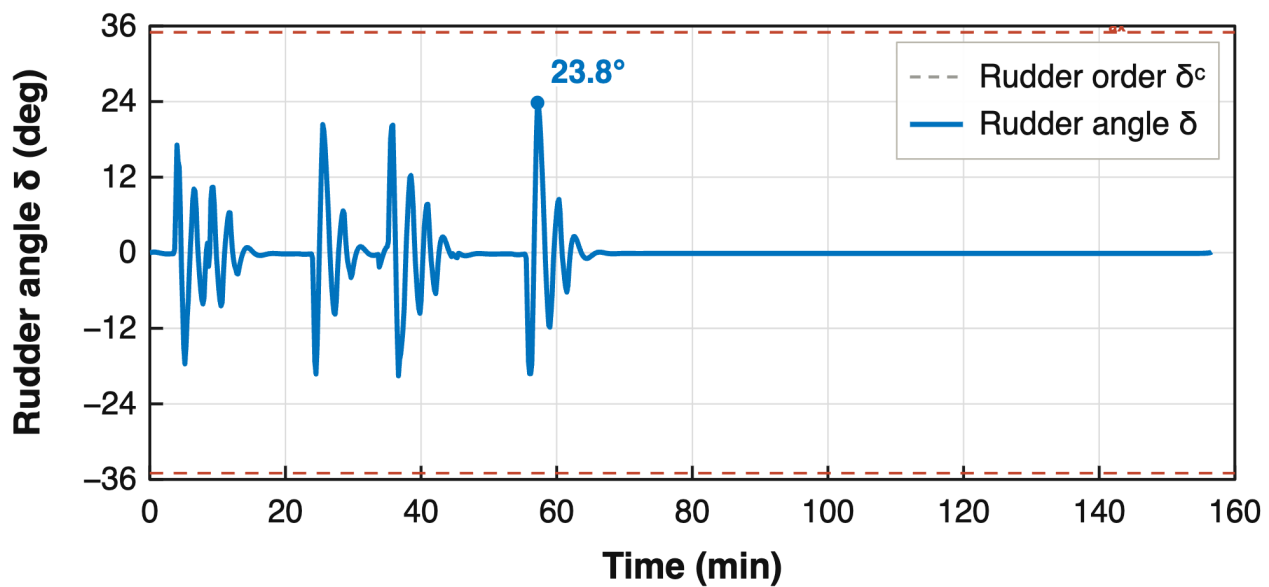


Figure 5 Rudder angle variations.

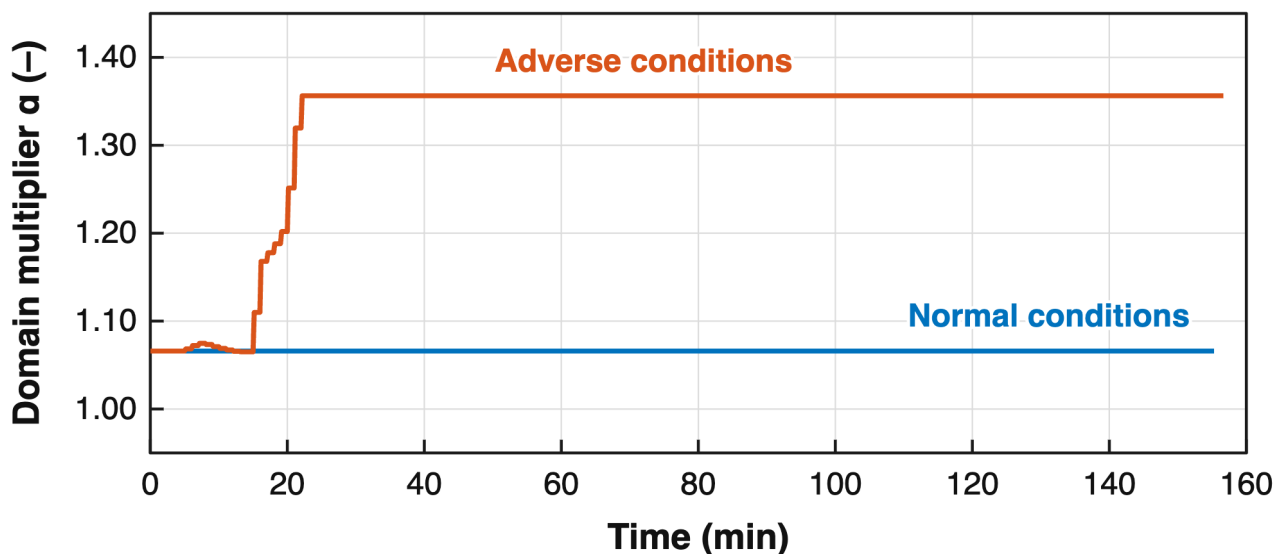


Figure 6 DM coefficient (α) over time: Normal vs. Adverse conditions.

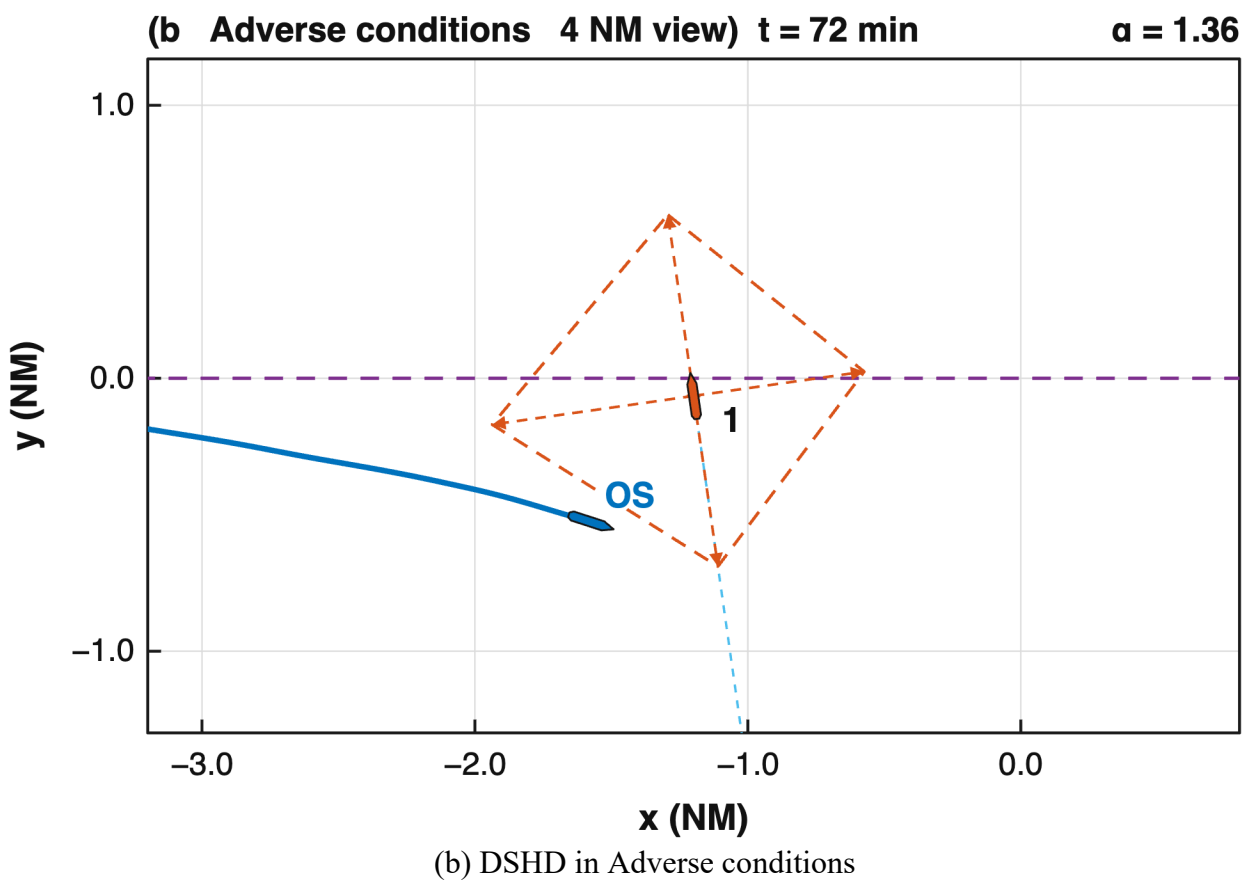
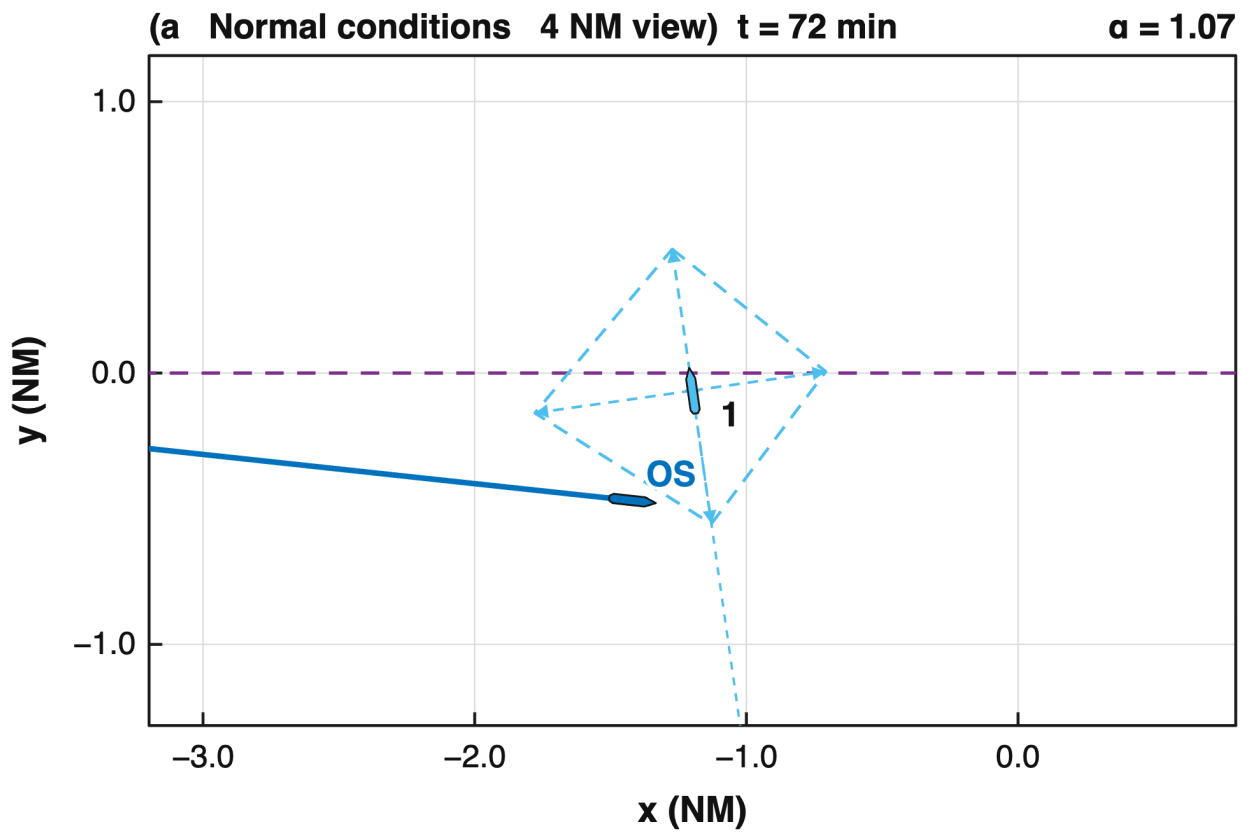


Figure 7 DSHD size over time: Normal and Adverse conditions.

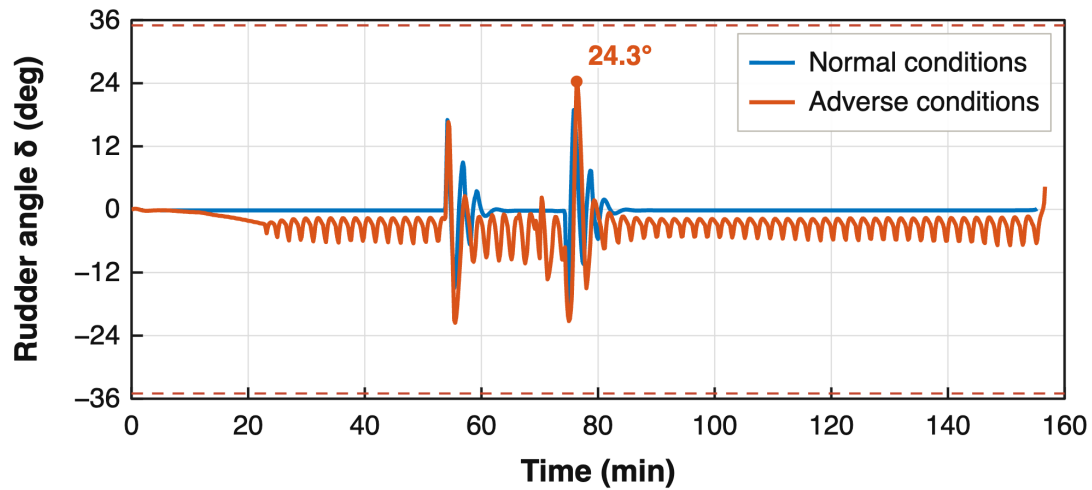


Figure 8 Rudder angle comparison.

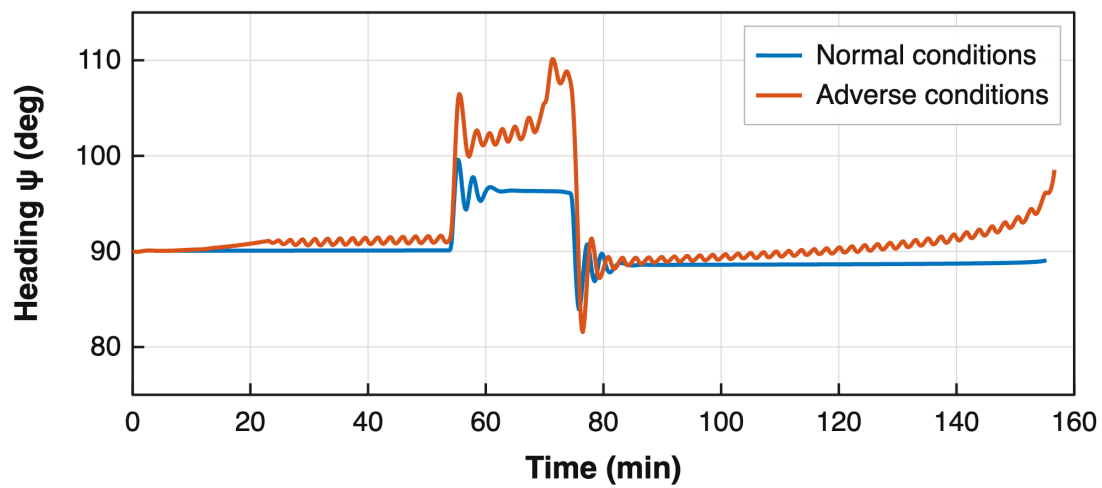


Figure 9 Heading comparison.

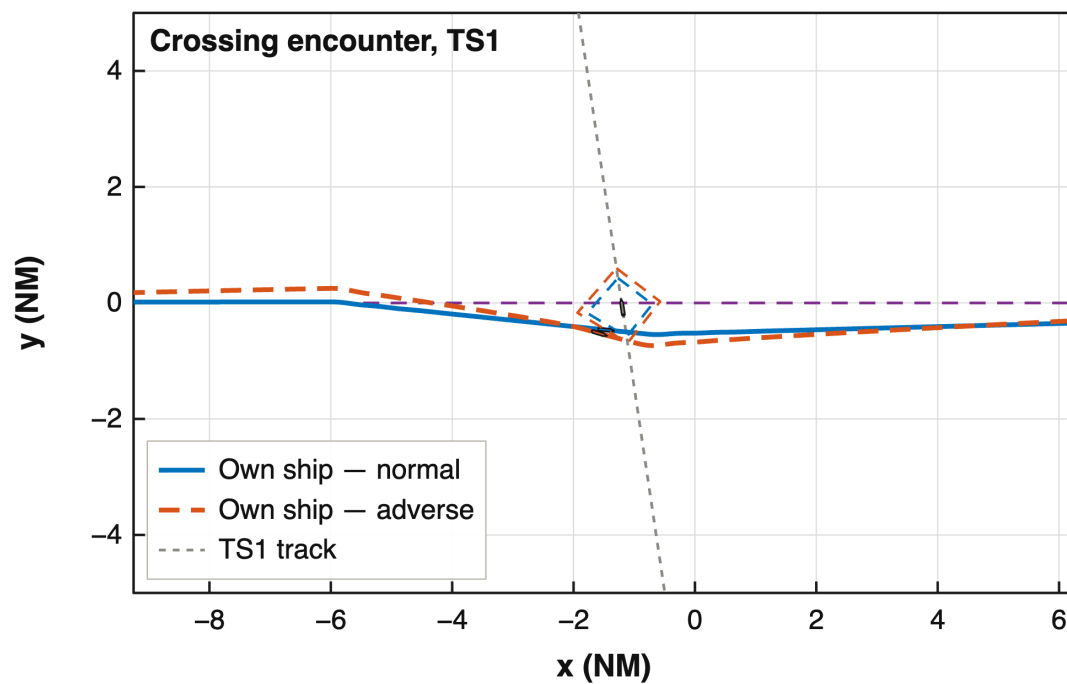


Figure 10 Trajectory comparison.

4. Discussion

The simulation results presented demonstrate that the proposed integrated system comprising the ACRAS, the DSHD model, and the COLREGs-compliant avoidance algorithm addresses several persistent limitations identified in the existing literature on ship collision risk assessment, ship domain modeling, and automatic collision avoidance maneuvering.

Regarding collision risk assessment, the foundational SHD concepts by Fujii and Tanaka(1971) and Goodwin (1975) established spatial safety boundaries as invariant geometric regions surrounding a vessel. Subsequent developments, including the multi-layer SHD by Luong and Im (Im & Luong, 2019; Luong et al., 2021) and the elliptical SHD by Yoo and Lee (2019), refined the domain geometry and incorporated additional input factors such as relative bearing and vessel characteristics, yet the resulting risk indices remained independent of meteorological conditions. The fuzzy-based approach by Fiskin (2023) employed 18 rules combining diverse inputs to compute hazardous zones; however, these rules were not disclosed, limiting reproducibility and independent verification. The ACRAS proposed in this study overcomes these limitations through a hierarchical five-stage fuzzy architecture containing 160 explicitly defined and verifiable rules, which simultaneously processes environmental inputs (wind force, wave height, visibility, and day/night condition) alongside geometric encounter parameters (DCPA and TCPA). This design extends the classical fuzzy CR approach of Hasegawa and Kouzuki (1987) which evaluated risk exclusively from kinematic parameters by coupling geometric CR with the independently computed Dynamic Risk Factor (DRF) from environmental inputs, producing a FCR that reflects both encounter geometry and environmental severity. The hierarchical decomposition also addresses the site-specificity limitation of data-driven approaches such as Zhang et al. (2021), whose hydrometeorological CR indices require historical AIS and weather databases for a particular geographic area, whereas the ACRAS encodes universal maritime risk principles (Beaufort Scale thresholds, IMO visibility categories) inherently transferable across operational regions.

Concerning ship domain models, the static or semi-static formulations prevalent in the literature (Chun et al., 2021; Du et al., 2021; Fujii & Tanaka, 1971; Goodwin, 1975; Yoo & Lee, 2019) do not respond to degraded vessel maneuvering capacity under adverse sea states. Du et al. (2021) proposed an empirical domain based on the vessel's first evasive maneuver point derived from AIS data in the Northern Baltic Sea, yet these domains remain fixed once established. The asymmetric elliptical SHD employed by Chun et al. (2021) defined a constant boundary with $CR = 1$ at the domain intersection. By contrast, the DSHD model introduces a multiplicative expansion coefficient α that dynamically scales all BLA dimensions in real time according to the DRF output. The Scenario 2 results confirmed that, under adverse conditions (Beaufort 6, visibility < 3 NM), α rose to ≈ 1.36 (measured range 1.06 - 1.36), automatically enlarging the safety domain without any manual parameter re-tuning. Critically, because α is governed exclusively by slowly-varying environmental variables rather than proximity-based metrics (TCPA, DCPA), the domain boundary remained stable throughout the avoidance maneuver, preventing the erratic command oscillations that proximity-driven dynamic domains could produce. This distinguishes the DSHD from the time-interactive SHD model by Zhang et al. (2025), which addresses temporal domain variability but does not incorporate environmental degradation effects on domain geometry.

With respect to collision avoidance maneuvering, heuristic approaches such as the evolutionary algorithm by Smierzchalski and Michalewicz (2000) and the Genetic Algorithm by Zeng (2003) optimized avoidance trajectories but either lacked explicit COLREGs integration or faced convergence time constraints limiting real-time applicability. APF-based methods (Liu et al., 2023; Lyu & Yin, 2019) and their hybrid variants (Chen et al., 2021; Sang et al., 2021) demonstrated real-time capability but remain susceptible to local minima entrapment. The DRL approaches by Jiang et al. (2022) and Li et al. (2021) represent emerging paradigms; however, their decision-making processes lack the interpretability and auditability demanded by maritime regulatory authorities for

safety-critical systems. The proposed algorithm addresses these issues through a deterministic optimal heading search evaluated by a three-term cost function encoding COLREGs Rules 13, 14, 15, and 17 as a continuous soft-penalty rather than a hard constraint. This formulation produces transparent, auditable decisions while maintaining real-time execution without iterative convergence requirements. The Scenario 1 results, where five overlapping collision threats were successfully resolved with peak rudder deflections of $\pm 23.8^\circ$ and full COLREGs compliance, demonstrate the effectiveness of the HCRSC priority mechanism in serializing multi-vessel avoidance tasks. This capability addresses the multi-vessel scalability concern noted for both the CNN-based approach by Zhang et al. (2020) and the SHD plotting challenges.

Furthermore, while direct empirical comparisons with other state-of-the-art methods, such as APF, VO, or DRL, often depend heavily on specific environmental parameter tuning and training configurations, the superiority and efficiency of the proposed system can be quantitatively established through its computational complexity and trajectory stability.

In terms of computational time and efficiency, grid-based heuristic algorithms and conventional APF methods frequently suffer from an exponential increase in search space or protracted iterative convergence during complex multi-vessel encounters. Conversely, the proposed deterministic algorithm operates entirely within a discretized one-dimensional search space (Ω_ψ). For N target ships and a fixed number of candidate headings M , the computational complexity per decision cycle is bounded by $O(M \times N)$. This linear $O(N)$ complexity ensures that the algorithm executes in merely a few milliseconds on standard marine processors, offering a drastically lower computational burden compared to the hardware-intensive requirements of DRL or the iterative demands of evolutionary algorithms.

Regarding trajectory deviation and safety margins, traditional APF models and hard-constrained optimization methods often exhibit severe chattering behavior when repulsive obstacle forces conflict with goal-seeking forces, leading to erratic rudder commands and fluctuating safety margins. By formulating COLREGs rules not as hard constraints but as continuous soft-penalties integrated into a three-term cost function (Eq. (12)) that explicitly penalizes inter-cycle command instability, the proposed closed-loop controller guarantees smooth, dynamically feasible heading transitions. This mechanism fundamentally prevents the sharp trajectory deviations typical of APF methods, ensuring that the dynamically expanded safety margins established by the DSHD remain inviolate and stable throughout the entire evasion and recovery phase.

A further limitation lies in the isotropic character of the expansion mechanism. The scalar α enlarges all four BLA dimensions uniformly, yet hydro-meteorological forces act on a ship with strong directionality. A severe crosswind induces a transverse drift that erodes the safety margin on the leeward side, whereas a headwind mainly lengthens the required stopping distance ahead. Under such directional encounters, a uniform enlargement may command more cautious maneuvers than the situation demands. Future work will therefore replace the scalar with a directional coefficient matrix derived by projecting the relative wind and wave vectors onto the surge and sway axes of the ship, so that the forward, aft, port, and starboard boundaries of the BLA scale independently with the asymmetry of the disturbance. This directional mechanism will be integrated with speed control and economic objectives to balance navigational safety against operational efficiency.

Collectively, the simulation results confirm that the tightly coupled ACRA-DSHD-avoidance architecture provides an integrated solution to three gaps identified in Section 1: the underestimation of collision risk under adverse meteorological conditions, addressed by the dual-chain FCR computation; the inability of static SHD boundaries to reflect degraded maneuvering capacity, addressed by the DRF-driven dynamic expansion mechanism; and the lack of validated integration between environmental risk assessment, adaptive safety domains, and COLREGs-compliant avoidance within a single coherent framework, demonstrated through multi-vessel encounter simulations under variable weather conditions.

5. Conclusions

This paper presented an integrated environment-adaptive automatic ship collision avoidance system coupling three components: the ACRAS, the DSHD model, and a COLREGs-compliant avoidance algorithm. The ACRAS employs a five-stage hierarchical fuzzy inference architecture with 160 rules to simultaneously process meteorological and geometric encounter inputs, producing a Dynamic Risk Factor that directly parameterizes the DSHD expansion coefficient α . The avoidance algorithm selects optimal headings through a three-term cost function balancing route deviation, maneuver stability, and COLREGs compliance (Rules 13, 14, 15, and 17). Simulation on the KVLCC2 model ($L = 320$ m) in MATLAB/Simulink demonstrated that the system successfully avoided all five target vessels with peak rudder deflections of $\pm 23.8^\circ$ and full regulatory compliance, while under adverse conditions (Beaufort 6, visibility < 3 NM) the expansion coefficient α autonomously rose to ≈ 1.36 , triggering wider avoidance maneuvers without parameter re-tuning. The current study has several limitations that define directions for future research. The validation relies exclusively on deterministic simulation; field trials on high-fidelity bridge simulators and instrumented vessels are required to establish operational reliability. In addition, the expansion mechanism remains isotropic, as the scalar α enlarges all four BLA dimensions uniformly while hydro-meteorological forces act directionally on the hull, and future work will replace it with a directional coefficient matrix that scales the forward, aft, port, and starboard boundaries independently.

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Declaration of generative AI in scientific writing

While preparing this manuscript, the authors employed ChatGPT and Claude to enhance the readability and improve the grammatical accuracy of certain sections and sentences. The use of ChatGPT and Claude is only to assist in the refinement of the text and language; we do not use ChatGPT or Claude to supplant any essential tasks. With or without AI applications, the authors are fully accountable for every process of the work and manuscript writing. All final edits, interpretations, and conclusions are the sole responsibility of the authors. The authors academically and ethically confirmed that the stated AI statements are true, and the authors are ultimately responsible and accountable for the contents of the published work, including the correctness of the references in the reference list.

CRedit contribution statement

Gia Huy Dinh: Conceptualization, Methodology, Formal analysis, Investigation, Data Curation, Writing - Review & Editing, Supervision; **Quoc Hai Dang:** Conceptualization, Methodology, Formal analysis, Investigation, Project administration, Writing - Original Draft; **Van Tien Nguyen:** Software, Validation, Formal analysis, Resources; **Minh Hieu Nguyen:** Methodology, Software, Validation, Formal analysis, Investigation; **Cong Minh Tran:** Investigation, Resources, Data Curation, Writing - Review & Editing; **Van Tung Nguyen:** Investigation, Resources, Visualization, Supervision.

References

- Aydin, M., Akyuz, E., Turan, O., & Arslan, O. (2021). Validation of risk analysis for ship collision in narrow waters by using fuzzy Bayesian networks approach. *Ocean Engineering*, 231, 108973. <https://doi.org/10.1016/j.oceaneng.2021.108973>

- Blaich, M., Rosenfelder, M., Schuster, M., Bittel, O., & Reuter, J. (2012). *Fast grid based collision avoidance for vessels using A* search algorithm* (pp. 385-390). In Proceedings of the 17th International Conference on Methods & Models in Automation & Robotics.
<https://doi.org/10.1109/MMAR.2012.6347858>
- Chen, Y., Bai, G., Zhan, Y., Hu, X., & Liu, J. (2021). Path planning and obstacle avoiding of the USV based on improved ACO-APF hybrid algorithm with adaptive early-warning. *IEEE Access*, 9, 40728-40742. <https://doi.org/10.1109/ACCESS.2021.3062375>
- Chun, D. H., Roh, M. I., Lee, H. W., Ha, J., & Yu, D. (2021). Deep reinforcement learning-based collision avoidance for an autonomous ship. *Ocean Engineering*, 234, 109216.
<https://doi.org/10.1016/j.oceaneng.2021.109216>
- Coldwell, T. G. (1983). Marine traffic behaviour in restricted waters. *Journal of Navigation*, 36(3), 430-444. <https://doi.org/10.1017/S0373463300039783>
- Davis, P. V., Dove, M. J., & Stockel, C. T. (1980). A computer simulation of marine traffic using domains and arenas. *Journal of Navigation*, 33(2), 215-222.
<https://doi.org/10.1017/S0373463300035220>
- Dinh, G. H., & Im, N. (2016). The combination of analytical and statistical method to define polygonal ship domain and reflect human experiences in estimating dangerous area. *International Journal of E-Navigation and Maritime Economy*, 4, 97-108.
<https://doi.org/10.1016/j.enavi.2016.06.009>
- Dinh, G. H., & Im, N. K. (2017). A study on the construction of stage discrimination model and consecutive waypoints generation method for ship's automatic avoiding action. *International Journal of Fuzzy Logic and Intelligent Systems*, 17(4), 294-306.
<https://doi.org/10.5391/IJFIS.2017.17.4.294>
- Du, L., Banda, O. A. V., Huang, Y., Goerlandt, F., Kujala, P., & Zhang, W. (2021). An empirical ship domain based on evasive maneuver and perceived collision risk. *Reliability Engineering & System Safety*, 213, 107752. <https://doi.org/10.1016/j.ress.2021.107752>
- Fiskin, R. (2023). An advanced decision-making model for determining ship domain size with a combination of MCDM and fuzzy logic. *Ocean Engineering*, 283, 114976.
<https://doi.org/10.1016/j.oceaneng.2023.114976>
- Fujii, Y., & Tanaka, K. (1971). Traffic capacity. *Journal of Navigation*, 24(4), 543-552.
<https://doi.org/10.1017/S0373463300022384>
- Goodwin, E. M. (1975). A statistical study of ship domains. *Journal of Navigation*, 28(3), 328-344.
<https://doi.org/10.1017/S0373463300041230>
- Hasegawa, K., & Kouzuki, A. (1987). Automatic collision avoidance system for ships using fuzzy control. *Journal of the Kansai Society of Naval Architects*, 205, 2.34-2.58.
<http://www.naoe.eng.osaka-u.ac.jp/~hase/cv/papers/013e.pdf>
- He, Z., Chu, X., Liu, C., & Wu, W. (2023). A novel model predictive artificial potential field based ship motion planning method considering COLREGs for complex encounter scenarios. *ISA Transactions*, 134, 58-73. <https://doi.org/10.1016/j.isatra.2022.09.007>
- Huang, Y., & Van Gelder, P. H. A. J. M. (2020). Collision risk measure for triggering evasive actions of maritime autonomous surface ships. *Safety Science*, 127, 104708.
<https://doi.org/10.1016/j.ssci.2020.104708>
- Im, N., & Luong, T. N. (2019). Potential risk ship domain as a danger criterion for real-time ship collision risk evaluation. *Ocean Engineering*, 194, 106610.
<https://doi.org/10.1016/j.oceaneng.2019.106610>
- Jiang, L., An, L., Zhang, X., Wang, C., & Wang, X. (2022). A human-like collision avoidance method for autonomous ship with attention-based deep reinforcement learning. *Ocean Engineering*, 264, 112378. <https://doi.org/10.1016/j.oceaneng.2022.112378>
- Kundakci, B., Nas, S., & Gucma, L. (2023). Prediction of ship domain on coastal waters by using AIS data. *Ocean Engineering*, 273, 113921. <https://doi.org/10.1016/j.oceaneng.2023.113921>

- Kuwata, Y., Wolf, M. T., Zarzhitsky, D., & Huntsberger, T. L. (2014). Safe maritime autonomous navigation with COLREGS, using velocity obstacles. *IEEE Journal of Oceanic Engineering*, 39(1), 110-119. <https://doi.org/10.1109/JOE.2013.2254214>
- Lazarowska, A. (2015). Ship's trajectory planning for collision avoidance at sea based on ant colony optimisation. *Journal of Navigation*, 68(2), 291-307. <https://doi.org/10.1017/S0373463314000708>
- Lazarowska, A. (2017). A new deterministic approach in a decision support system for ship's trajectory planning. *Expert Systems with Applications*, 71, 469-478. <https://doi.org/10.1016/j.eswa.2016.11.005>
- Lee, C. Y. (1961). An algorithm for path connections and its applications. *IEEE Transactions on Electronic Computers*, 10(3), 346-365. <https://doi.org/10.1109/TEC.1961.5219222>
- Li, L., Wu, D., Huang, Y., & Yuan, Z. M. (2021). A path planning strategy unified with a COLREGS collision avoidance function based on deep reinforcement learning and artificial potential field. *Applied Ocean Research*, 113, 102759. <https://doi.org/10.1016/j.apor.2021.102759>
- Liu, W., Qiu, K., Yang, X., Wang, R., Xiang, Z., Wang, Y., & Xu, W. (2023). COLREGS-based collision avoidance algorithm for unmanned surface vehicles using modified artificial potential fields. *Physical Communication*, 57, 101980. <https://doi.org/10.1016/j.phycom.2022.101980>
- Liu, Z., Zhang, B., Zhang, M., Wang, H., & Fu, X. (2023). A quantitative method for the analysis of ship collision risk using AIS data. *Ocean Engineering*, 272, 113906. <https://doi.org/10.1016/j.oceaneng.2023.113906>
- Luong, T. N., Hwang, S., & Im, N. (2021). Harbour traffic hazard map for real-time assessing waterway risk using marine traffic hazard index. *Ocean Engineering*, 239, 109884. <https://doi.org/10.1016/j.oceaneng.2021.109884>
- Lyu, H., & Yin, Y. (2019). COLREGS-constrained real-time path planning for autonomous ships using modified artificial potential fields. *Journal of Navigation*, 72(3), 588-608. <https://doi.org/10.1017/S0373463318000796>
- Mitrofanov, O. (1968). An anti-collision indicator. *Journal of Navigation*, 21(2), 163-170. <https://doi.org/10.1017/S0373463300030319>
- Murray, B., & Perera, L. P. (2021). An AIS-based deep learning framework for regional ship behavior prediction. *Reliability Engineering & System Safety*, 215, 107819. <https://doi.org/10.1016/j.ress.2021.107819>
- Pietrzykowski, Z. (2008). Ship's fuzzy domain: A criterion for navigational safety in narrow fairways. *Journal of Navigation*, 61(3), 499-514. <https://doi.org/10.1017/S0373463308004682>
- Pietrzykowski, Z., & Uriasz, J. (2009). The ship domain: A criterion of navigational safety assessment in an open sea area. *Journal of Navigation*, 62(1), 93-108. <https://doi.org/10.1017/S0373463308005018>
- Rawson, A., Rogers, E., Foster, D., & Phillips, D. (2014). Practical application of domain analysis: Port of London case study. *Journal of Navigation*, 67(2), 193-209. <https://doi.org/10.1017/S0373463313000684>
- Sang, H., You, Y., Sun, X., Zhou, Y., & Liu, F. (2021). The hybrid path planning algorithm based on improved A* and artificial potential field for unmanned surface vehicle formations. *Ocean Engineering*, 223, 108709. <https://doi.org/10.1016/j.oceaneng.2021.108709>
- Sawada, R., Sato, K., & Majima, T. (2021). Automatic ship collision avoidance using deep reinforcement learning with LSTM in continuous action spaces. *Journal of Marine Science and Technology*, 26(2), 509-524. <https://doi.org/10.1007/s00773-020-00755-0>

- Silveira, P., Teixeira, A. P., & Guedes Soares, C. (2022). A method to extract the Quaternion Ship Domain parameters from AIS data. *Ocean Engineering*, 257, 111568.
<https://doi.org/10.1016/j.oceaneng.2022.111568>
- Smierzchalski, R., & Michalewicz, Z. (2000). Modeling of ship trajectory in collision situations by an evolutionary algorithm. *IEEE Transactions on Evolutionary Computation*, 4(3), 227-241.
<https://doi.org/10.1109/4235.873234>
- Szlapczynski, R. (2015). Evolutionary planning of safe ship tracks in restricted visibility. *Journal of Navigation*, 68(1), 39-51. <https://doi.org/10.1017/S0373463314000587>
- Ugurlu, H., & Cicek, I. (2022). Analysis and assessment of ship collision accidents using fault tree and multiple correspondence analysis. *Ocean Engineering*, 245, 110514.
<https://doi.org/10.1016/j.oceaneng.2021.110514>
- Wang, N. (2013). A novel analytical framework for dynamic quaternion ship domains. *Journal of Navigation*, 66(2), 265-281. <https://doi.org/10.1017/S0373463312000483>
- Wang, N., Meng, X., Xu, Q., & Wang, Z. (2009). A unified analytical framework for ship domains. *Journal of Navigation*, 62(4), 643-655. <https://doi.org/10.1017/S0373463309990178>
- Yoo, Y., & Lee, J. S. (2019). Evaluation of ship collision risk assessments using environmental stress and collision risk models. *Ocean Engineering*, 191, 106527.
<https://doi.org/10.1016/j.oceaneng.2019.106527>
- Zeng, X. (2003). Evolution of the safe path for ship navigation. *Applied Artificial Intelligence*, 17(2), 87-104. <https://doi.org/10.1080/713827101>
- Zhang, M., Montewka, J., Manderbacka, T., Kujala, P., & Hirdaris, S. (2021). A big data analytics method for the evaluation of ship: Ship collision risk reflecting hydrometeorological conditions. *Reliability Engineering & System Safety*, 213, 107674.
<https://doi.org/10.1016/j.ress.2021.107674>
- Zhang, W., Feng, X., Goerlandt, F., & Liu, Q. (2020). Towards a convolutional neural network model for classifying regional ship collision risk levels for waterway risk analysis. *Reliability Engineering & System Safety*, 204, 107127.
<https://doi.org/10.1016/j.ress.2020.107127>
- Zhang, Z., Zhao, H., Wang, J., & Wang, H. (2025). Efficient collaborative collision avoidance algorithm considering COLREGs in complex multi-ship encounter scenarios. *Applied Ocean Research*, 163, 104753. <https://doi.org/10.1016/j.apor.2025.104753>
- Zheng, K., Chen, Y., Jiang, Y., & Qiao, S. (2020). A SVM based ship collision risk assessment algorithm. *Ocean Engineering*, 202, 107062.
<https://doi.org/10.1016/j.oceaneng.2020.107062>
- Zhou, W., Zheng, J., & Xiao, Y. (2022). An online identification approach for ship domain model based on AIS data. *Plos One*, 17(3), e0265266.
<https://doi.org/10.1371/journal.pone.0265266>