



**Robust Decision Making for the Reactive
Collision Avoidance of Maritime Autonomous
Surface Ships**

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A thesis submitted for the degree of Doctor of
Philosophy

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Signed: Paul Lee

Date: 20th August, 2024

“Thirst was made for water; inquiry for truth.”

C.S. Lewis, 1898–1963

Acknowledgements

This is the original work of the author for the degree of Doctor of Philosophy (PhD), a four-and-a-half-year-long research since February 2020 that finally comes to an end. I started my PhD as a fresh graduate from an Integrated Master's course, as a temporary refuge from my overwhelming anxieties about my career and future in general, without fully grasping what research entails, ignorant of what to expect. During my PhD course – which as often said is more like a marathon than a sprint – my weaknesses, failures, and strengths became more apparent, I came to hate but ended up loving doing research, and found my passion. I learned how to carry on my own project from scratch to finish that fostered my independence; learned how to think, write, and communicate novel ideas that cultivated my worldview to become more systematic and creative; and even learned how to code, which was one of my biggest weaknesses and fears, but naturally introduced me to the world of artificial intelligence that ended up bolstering my self-confidence for any future challenges to come. But most importantly, I grew as a person and in character to become a man of prayer before God and a man of humility before my sins and weaknesses, till I eventually confessed that indeed ‘*Man shall not live by bread alone, but by every word that proceedeth out of the mouth of God*’ (Matthew 4:4, KJV). Thus, despite the countless challenges I faced – that space and time do not allow to be written down here – I would still choose to take the same path if I ever had the chance to rewrite my story; though it all started out of ignorance it was a journey worth taking.

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Abstract

The maritime industry is expected to utilize maritime autonomous ships (MASSs) to realise new sustainability levels, but their ability to make robust decisions without human intervention during safety-critical operations, such as collision avoidance, remains a challenge.

This research aims to propose a holistic methodology that enhances the robustness of decision making for the reactive collision avoidance of a MASS from design to operation. In the first phase, the risk-informed design of the collision avoidance system (CAS) is conducted to reduce critical internal collision risk indices (CRIs). In the second phase, a digital twin environment is developed to simulate critical collision scenarios pertaining to internal CRIs-based dynamic safety domain, propeller-rudder coupled control, noisy perception sensor, critically proximate and unclassified static or dynamic obstacles. In the third phase, a decision-making agent is optimised for the reactive collision avoidance operation within the above scenarios in a deep reinforcement learning (DRL)-based training framework. In the fourth phase, a classification agent is optimised for the identification of static or dynamic obstacles based on real-time perception sensor data in a deep learning training framework. In the fifth phase, the robustness of decision-making is quantified, verified, and validated within and outside the investigated scenarios.

Fault tree analysis, deep deterministic policy gradient algorithm, and feedforward neural networks are employed for the risk analysis, DRL-, and DL-based training frameworks, respectively. A high-speed single screw container ship and a light detection and ranging (LIDAR) sensor are considered for the reference ship. The results demonstrate that a risk-informed design conducted from a cost-benefit perspective leads up to 91% reduction of the CAS probability of failure from its baseline configuration. Robustness of decision-making agent for the reactive collision avoidance is verified even when the safety domain and LIDAR noise is increased by 20% and 132% from its maximum trained value, respectively, and the size of the critically proximate static obstacle and size of the static or dynamic obstacle is increased by 200% and decreased by 88.5% from its trained value, respectively. The ability of the decision-making agent to prioritise safety over efficiency depending on the size of

the safety domain and LIDAR noise level, conduct sophisticated propeller-rudder coupled control manoeuvres when encountered with critically proximate static obstacles, and conduct efficient or navigational rules-compliant evasive manoeuvres when encountered with static or dynamic obstacles are noted. The accuracy of the classification agent is verified above 98.12% even in different LIDAR configurations.

The novelty of this research stems from the introduction of a framework that enhancing the safety against the unknown-unknowns by increasing the robustness against critical CRIs, such as system probability of failure, uncertainty of sensor measurements, collision-inducing obstacles, and limited information. This research contributes towards the development of safe maritime autonomous systems that are capable of making robust decisions under safety-critical scenarios.

Research Output

Journal Papers

Lee P., Theotokatos G., Boulougouris E. (2024). Robust decision-making for the reactive collision avoidance of autonomous ships against various perception sensor noise levels. *Journal of Marine Science and Engineering*. <https://doi.org/10.3390/jmse12040557>

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Conference Papers

Lee P., Bolbot V., Theotokatos G., Boulougouris E., & Dracos, V. (2021). Fault tree analysis of the autonomous navigation for maritime autonomous surface ships. *Proceedings of the 1st International Conference on the Stability and Safety of Ships and Ocean Vehicles 2021*, Glasgow, United Kingdom. <https://strathprints.strath.ac.uk/76923/>

Lee P., Theotokatos G., & Boulougouris E. (2021). Robust Autonomous Collision Avoidance Decision Making System for Maritime Autonomous Surface Ships. Presented at *International Maritime and Port Technology and Development Conference and 4th International Conference on Maritime Autonomous Surface Ships 2022*, Singapore. <https://strathprints.strath.ac.uk/76923/>

Awards

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Louvros P., Zhao W., Lee P., Arcidiacono M., Gorska K., Tsoumpris C., Dixon A., Ohol N., Wright M., Troll M., Iqbal M., Ameer M-A-A., Stefanou E., Aung M-Z., Dai S., Jia L., & Theotokatos G. (2023). Njord Competition Technical Report Team: Strath Voyager. Team Spirit award at *Njord - The Autonomous Ship Challenge, 2023*, Trondheim, Norway. https://pure.strath.ac.uk/admin/files/176652901/Njord_Competition_2023_Technical_Report.pdf

Lee P., Theotokatos G., Evangelos B. (2022). Trustworthy Autonomous Collision Avoidance Decision-Making System for Maritime Autonomous Surface Ships. Young Researcher Competition 2nd prize award in Waterborne Transport Category at *TRAVISIONS 2022*, Lisbon, Portugal. https://www.travisions.eu/TRAVisions/young_researcher_results_2022/

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Acronyms & List of Symbols

Acronyms

2D	Two dimensions	DMS	Decision-making system
3D	Three dimensions	DNN	Deep neural network
3DOF	Three degrees of freedom	DNV	Det Norske Veritas
4DOF	Four degrees of freedom	DQN	Deep Q network
AES	Action execution system	DRL	Deep reinforcement learning
AI	Artificial intelligence	DW	Dynamic window
AIS	Automatic identification system	ECDIS	Electronic chart display and information system
APF	Artificial potential field	EU	European Union
BE	Basic event	FL	Fuzzy logic
BM	Birnbaum importance metric	FNN	Feedforward neural network
BN	Bayesian network	FPVO	Fast probabilistic velocity obstacle
BV	Bureau Veritas	FT	Fault tree
CAS	Collision avoidance system	FTA	Fault tree analysis
CCS	China Classification Society	FV	Fussell-Vesely importance metric
CFD	Computational fluid dynamics	GNSS	Global navigation satellite system
ClassNK	Nippon Kaiji Kyokai	ICS	Intention communication system
COLREG	International Regulations for Preventing Collisions at Sea	IE	Intermediate event
CPA	Closest point of approach	IMO	International Maritime Organisation
CPS	Cyber-physical system	INS	Inertial navigation system
CR	Criticality importance metric	KET	Key enabling technology
CRI	Collision risk index	KR	Korean Register
DCPA	Distance to closest point of approach	LIDAR	Light detection and ranging
DDPG	Deep deterministic policy gradient	LR	Lloyd's Register
DL	Deep learning	MASS	Maritime autonomous surface ship
		MCS	Minimal cut set

MDP	Markov decision process	$\mathcal{G}_t$	Return at time t
MMG	Manoeuvring modelling group	$\mathcal{N}$	Noise variance observation
MPC	Model predictive control	$\mathcal{Q}_{TE}(t)$	Probability of a top event occurring at time t
MSC	Maritime Safety Committee		
MTBF	Mean time between failure	$\mathcal{T}$	Terminal timestep
OS	Own ship	$\mathcal{W}$	Noise process
PD	Proportional derivative	$\overline{GM}$	Metacentric height
PPO	Proximal policy optimisation	Θ	Relative angle
PSO	Particle swarm optimisation	a_μ	Learning rate of the actor network
R&D	Research and development	a_Q	Learning rate of the critic network
RADAR	Radio detection and ranging	A_t	Action at time t
RCC	Remote control centre	a_t	Value of the action at time t
SAS	Situation awareness system	a_{y_B}	x_B -coordinate of centre of m_{y_B}
SMCR	Specified maximum continuous rating	b	Size of the minibatch
SOLAS	International Convention for the Safety of Life at Sea	c	Speed of light
SONAR	Sound navigation and ranging	d	LIDAR distance measurement
SSS	Short-sea shipping	e_H	Heading error
STPA	System-theoretic process analysis	G	Centre of gravity
TCPA	Time to closest point of approach	I^{BM}	Birnbaum importance metric
TD3	Twin delayed DDPG	I^{CR}	Criticality importance metric
TE	Top event	I^{FV}	Fussell-Vesely importance metric
TS	Target ship	I_{x_B}	Moment of inertia about the x_B -axis
V&V	Verification and validation	I_{z_B}	Moment of inertia about the z_B -axis
VO	Velocity obstacle	J	Expected return
XT	Cross track	J_{x_B}	Added moment of inertia in the x_B -axis
XTL	Cross track limit	J_{z_B}	Added moment of inertia in the z_B -axis
Symbols		K	Roll moment about the centre of gravity
$\check{Q}_j(t)$	Probability of the j^{th} minimal cut set that can be derived from the probability of an event with only an and-gate	k	Coefficient
$\dot{n}$	Propeller revolution rate	L	Loss function
$\mathcal{B}$	Minibatch	l_{x_B}	z_B -coordinate of centre of m_{x_B}
$\mathcal{D}$	Replay buffer	l_{y_B}	z_B -coordinate of centre of m_{y_B}
		m	Ship's mass
		m_{x_B}	Added mass in the x_B direction
		m_{y_B}	Added mass in the y_B direction

N	Yaw moment about the midship	GHz	Gigahertz
n	Propeller revolution	h	Hour
n_C	Commanded propeller revolution	km	Kilometre
o_0	Origin of the space-fixed coordinate system	kW	Kilowatt
		m	Metre
o_B	Origin of the body-fixed coordinate system	NM	Nautical miles
		rpm	Revolution per minute
OS	Obstacle classification	s	Second
POF	Probability of failure	tn	Tonnes
Q	Action-value function	Greek Symbols	
$q_i(t)$	Probability of the i^{th} basic event occurring at time t	β	Drift angle
		δ	Rudder angle
$q_i^o(t)$	Probability of the i^{th} basic event not occurring at time t	δ_C	Commanded rudder angle
		$\dot{\delta}$	Actual rudder deflection rate
r	Yaw rate	$\dot{\phi}$	Roll rate
R_t	Reward at time t	$\dot{\psi}$	Yaw rate
r_t	Value of the reward at time t	ϵ	Added noise
RM	Robustness metric	γ	Discount rate
s_t	Value of the state at time t	$\mathcal{E}$	Environment in an Markov decision process
SD	Safety domain		
t	Time	μ	Deterministic policy
T_δ	Time constant for the rudder angle	ϕ	Roll angle
T_n	Time constant for the propeller revolution	π	Policy
		ψ	Heading angle
TH	Threshold	σ^2	Variance
U	Resultant velocity	τ	Target smooth factor
u	Surge velocity	θ^μ	Parameterised weight of the actor network
v	Sway velocity		
W	Weight of water displaced by the ship hull	θ^Q	Parameterised weight of the critic network
X	Forces in the x_B -axis	Subscripts	
Y	Forces in the y_B -axis	B	Body
y	Target of the critic network	C	Command
deg	Degree	CA	Collision avoidance

CAE	Collision avoidance efficiency	min	Minimum
CC	COLREG-compliance	nom	Nominal
H	Heading	PF	Path following
max	Maximum	WP	Waypoint

Chapter 1

Introduction

1.1 Background

1.1.1 Towards Shipping 4.0

Maritime shipping is the backbone of the world's trade and globalisation [1]. Over 80% of international trade's volume and 70% of its value are waterborne with an average growth rate of 3.3% since 2000 [2], as it is by far the most dependable, efficient, and cost-effective mode of transportation [3]. It has an indisputable strategic position to improve people's life quality by providing access to essential commodities, such as food and energy, reduce environmental impact by enhancing fuel efficiency per t-km freight services, and stimulate economic growth by enabling cross-border trade liberalisation between developed and developing countries [4]. Thus, maritime shipping is considered to be one of the lifelines to realise global sustainability, such as the sustainable development goals set by the United Nations [5].

Since the early 2010s, the vision for a more sustainable future combined with the paradigm of industry 4.0 have paved the way towards the transition of the traditional maritime shipping to the new Shipping 4.0 era [6]. Shipping 4.0 describes the fully interconnected maritime ecosystem characterised by the increased digitalisation enabled through key enabling technologies (KETs), such as internet of things, cloud computing, big data analytics, virtual and augmented reality, cyber security, additive manufacturing, and artificial intelligence (AI) [7]. The leverage of such KETs is envisioned to create an ecosystem of cyber-physical systems (CPSs) that link their

physical entities to the digital world with locally embedded intelligence [8] to enable communication, monitoring, decision-making, and control in a decentralised and distributed manner [7].

The main building blocks of shipping 4.0 that encompass ecosystems of CPSs are the next-generation ships, known as cyber-enabled ships [7]. Specifically, a cyber-enabled ship can be a conventional one that adopts increased computerised and monitoring systems with remotely controlled and automated tasks or an autonomous one that integrates onboard systems with decision-making capabilities creating its own category of smart or autonomous ships, respectively [9]. Suffice it to say, the category of autonomous ships, also known as maritime autonomous surface ships (MASSs), is the most advanced and challenging one, as higher degrees of autonomy translate into increased decision-making responsibilities transferred on intelligent systems with less human intervention [10]. And whether the future maritime scene will be occupied by fully autonomous MASSs *‘is not a question of if it will happen but when’* [11].

Definition 1. (MASS) MASS is *‘a ship which, to a varying degree, can operate independent of human interaction’* [12].

1.1.2 MASS Initiatives

Both the academia and industry have been the frontiers of this fully autonomous vision by conducting large-scale research and development (R&D) projects related to MASSs. The first one in this field was the €3.9 million maritime unmanned navigation through intelligence in networks 2012–2015 [13] that aimed at initiating the idea of unmanned shipping in the European Union (EU) by developing a technical concept for the operation of a dry bulk carrier MASS and assessing its feasibility. The autonomous shipping initiative for European waters 2019–2023 [14] was by far the largest one of €30 million that aimed at propelling the transition towards MASSs in EU through the demonstration of two technology readiness level 7 or above fully autonomous MASS prototypes for short sea shipping and inland water ways with expected commercial application by the end of 2023. Other related R&D projects include the €7.9 million novel iwt and maritime transport concepts 2017–2021 [15], €7.5 million advanced efficient and green intermodel systems 2020–2023 [16], €15

million safe, efficient and autonomous: multimodal library for European shortsea and inland solutions 2023–2026 [17], and more.

In addition, major industrial efforts have been underway towards commercial applications [18], as the MASS market is projected to reach \$8.2 billion by 2030 with an annual growth rate of 9.6% over a decade [19]. Small-scale MASSs have already been used for research, scientific, or military purposes, such as for hydrographic measurements, water sampling, or surveillance [18], whereas large-scale ones have been limited only to demonstrations and sea trials. In 2018, Rolls-Royce with Finferries demonstrated autonomous navigation of the Falco 53.8 m car ferry between the Finnish coastlines of Parainen and Nauvo relying on sensor fusion and AI technologies for collision avoidance [20]. In 2019, Nippon Yusen Kaisha conducted the world’s first sea trial for the autonomous navigation of the Iris Leader pure car and truck carrier vessel from Xinsha, China to Yokohama, Japan [21]. In 2022, Hyundai Heavy Industries demonstrated the world’s first transoceanic autonomous navigation of the Prism Courage ultra-large liquified natural gas carrier from the Gulf of Mexico to Korea realising 7% fuel efficiency and 100 executions of autonomous collision avoidance [22]. Other industrial initiatives include the advanced autonomous waterborne applications [23], Yara Birkeland [24], Meguri2040 [25], Korean autonomous surface ship [26], and more.

Finally, the regulatory and classification bodies have been moving towards adopting MASSs within their frameworks but at a slower pace [27]. Specifically, in 2019, the Maritime Safety Committee’s (MSC) 101st session approved interim guidelines for MASS trials [28]. In 2021, MSC’s 103rd session completed a regulatory scoping exercise on MASSs by assessing existing International Maritime Organization (IMO) instruments in order to integrate new and advancing technologies in its regulatory framework [12]. In 2022, the MSC’s 106th session made further progress to adopt a non-mandatory goal-based MASS Code by 2025 and enter into force a mandatory one on 1 January 2028 [29]. On the other hand, classification societies have defined their own views on MASSs in forms of high-level guidelines, such as Det Norske Veritas [30], China Classification Society (CCS) [31], Lloyd’s Register (LR) [32], American Bureau of Shipping [33], Bureau Veritas (BV) [34, 35], Nippon Kaiji Kyokai (ClassNK) [36], and Korean Register (KR) [37]. In addition, some MASS prototypes and their frameworks have been awarded with approval in principle certifications from these societies, such as the DAN-V by KR [38], APExS-auto by ClassNK and BV [39], Zhuhai Cloud

by CCS [40], and AP24 by LR [41]. Thus, an unprecedented momentum has been propagated from all fronts of research, technology, and legislation towards adopting MASSs.

1.2 Problem Statement

1.2.1 Collision Avoidance Challenges

Prior to the full-scale adoption of MASSs, major challenges pertaining to safety-critical operations need to be addressed, from which collision avoidance is deemed to be one of the most demanding ones [42]. In particular, collision avoidance of large ships is an intrinsically demanding operation with multifaceted challenges considering the control of underactuated vessels of large inertia, the dynamic changes of the sea medium, and navigation among other ships [43]. In addition, the hostile maritime environment during adverse weather conditions and complex traffic scenarios due to the increase of the world fleet's number and sizes add another layer of challenges [8]. Thus, collision avoidance requires complex multi-tasking and cognitively demanding endeavours based on expert knowledge, good seamanship, compliance to navigation rules, correct interpretation of other ships' intentions, timely reaction, management of emergency situations, and more [44].

Moreover, global maritime accident statistics indicate that navigational accidents are the most common ones, including collision, grounding, and contact [45]. Particularly, analysis of those accidents from 2001 to 2020 indicates that collision is the leading accident category constituting as much as 64% followed by grounding with 14% [46]. Suffice it to say, such accidents have detrimental consequences in terms of human life loss, environmental pollution, and financial damage [47]. For instance, the collision accident of the Sanchi oil tanker in 2018 with the CF Crystal cargo ship resulted in the life loss of all Sanchi's 32 crew members, 138,000 t leakage of condensate and fuel oil into the ocean, and \$70 million and \$30 million loss for the cargo and vessel, respectively, becoming the most polluting oil tanker accident of the 21st century [48]. The grounding accident of the Ever Given 20,150 TEU container ship in 2021 caused the blockage of the Suez Canal and 422 cargo vessels for 6 days that were carrying an estimated \$9.6 billion worth of trade daily, such as

oil, consumer goods, commodities, and essential medical supplies for the coronavirus pandemic [49]. More recently, the collision of the MV Dali container ship with the Francis Scott Key bridge in 2024 led to the life loss of 6 bridge workers and collapse of the bridge that prohibited the passage of around 35,000 vehicles per day and economic activity of 15,000 workers in the Port of Baltimore, 140,000 related jobs, and \$6 billion loss of trade in a single month [50, 51].

Though it is hard to predict apriori what the consequences of the adoption of MASSs will be on the safety of the maritime scene, the emergence of new challenges is inevitable [52]. Particularly, despite human error accounting for 94.7% of collision accidents [53], human contribution to accident mitigation, though not reported, cannot be underestimated [54] and how MASSs will adapt to prior unknown collision-inducing situations without humans onboard is uncertain [55]. Moreover, the ability of MASSs to comprehend ambiguous human behaviours, such as good seamanship, remains open [18]. Finally, the scepticism of the public towards ethical and safety concerns related to MASSs and the current outline of general navigational rules that take into account only conventional ships for ship-to-ship encounters render the coexistence of conventional ships and MASSs highly debatable [56]. Thus, systematic research to investigate and address the challenges pertaining to the collision avoidance of MASS is a pressing need.

Definition 2. (*Collision avoidance*) *Collision avoidance is 'a process of departing from its planned trajectory to avoid a potential undesired physical contact at a certain time in the future' [57].*

1.3 Research Scope

1.3.1 Reactive Collision Avoidance

The aforementioned challenges pertaining to the collision avoidance of MASSs can be boiled down to the fundamental problem of optimal decision-making, such as pertaining to regulations, design, and operation, under risk [58]. Specifically, depending on the level of the decision-maker's knowledge about each risk, they can be categorised based on two factors, which are the level of available information

to the decision-maker and level of comprehensibility by the decision-maker [59], as presented in Table 1.1. Known-knowns are related to available information that can be comprehended, known-unknowns are related to unavailable information that can be predicted and comprehended, unknown-knowns are related to available information that cannot be comprehended, and unknown-unknowns are related to unavailable information that cannot be comprehended. Suffice it to say, the most critical ones that jeopardise the safety of MASSs are the risks emerging from the unknown-unknowns, such as unpredictable collision events.

Table 1.1 Risk categories.

	Available information to the decision-maker	Unavailable information to the decision-maker
Comprehensible information by the decision-maker	Known-knowns	Known-unknowns
Incomprehensible information by the decision-maker	Unknown-knowns	Unknown-unknowns

Various search strategies can be conducted that explore the unknown-unknowns to bring them into the realms of knowns by converting them into known-knowns, but such actions exhibit inevitable difficulties of ambiguity, unpredictability, and unexpectedness that render them time-consuming and ineffective [60]. A more efficient and effective way against the unknown-unknowns is to enhance the reactivity of MASSs in the presence of collision risk as an added safety measure [59]. Among the various global to local collision avoidance approaches [61], global ones rely on known-knowns, such as global map, where reactivity to unknown-unknowns cannot be achieved due to the reliance on ideal assumptions and deterministic collision risk. On the other hand, reactive collision avoidance is the most local approach that focuses on real-time decision-making at the lowest level of actuators' control without relying on known-knowns, such as based on locally detected collision risk using onboard sensors, which exhibits the ability to enhance the reactivity of MASSs against the unknown-unknowns emerging amidst the dynamic and uncertain maritime environment with often limited source of information [62]. Thus, a few research questions that naturally emerge are "how can the reactive collision avoidance of MASSs be enhanced? How can the robustness of reactive collision avoidance under different critical collision scenarios be secured?"

Definition 3. (*Risk*) Risk is 'the consequences of a future activity with respect to

something that humans value. The consequences are often seen in relation to some reference values and the focus is often on negative, undesirable consequences’ [63] or ‘the combined answer to the following three questions: 1. What can go wrong? 2. How probable is it? 3. What are the consequences?’ [64].

Definition 4. *(Collision risk) Collision risk is the risk due to the failure of collision avoidance.*

Definition 5. *(Reactive collision avoidance) Reactive collision avoidance is a subcategory of collision avoidance, where the process of collision avoidance is initiated as a dynamic response to an unpredictable collision risk due to its sudden emergence or rate that exceeds the predictable threshold.*

Definition 6. *(Critical collision scenario) Critical collision scenario is the degree of unique dynamic responses available to the ship responding to the collision risk without failure of reactive collision avoidance.*

Definition 7. *(Robustness) Robustness is the ‘magnitude of tolerability of a system against disturbances until a set requirement or threshold is violated’ [65, 66].*

1.4 Aim & Objectives

The aim of this research is to propose a holistic methodology from design to operation that enhances the robustness of decision making for the reactive collision avoidance of MASSs under critical collision scenarios. Specifically, robustness is investigated for any disturbance emerging from a critical collision scenario necessitating reactive collision avoidance of a MASS. The high-level objectives identified to address the aim of this research are as follows.

1. Design a collision avoidance system (CAS) considering risk-informed approaches for safe system design.
2. Develop and customise trustworthy digital twins for high-fidelity collision scenarios simulation.
3. Develop a decision-making tool for the reactive collision avoidance operation of MASSs.

4. Quantify, verify, and validate the robustness of decision making in critical collision scenarios.

1.5 Dissertation Layout

The layout of this dissertation is structured into seven chapters, an overview of which is provided as follows.

Chapter 1: An introduction to the new shipping 4.0 era, MASS initiatives, and challenges of collision avoidance for MASSs are presented. In addition, the research question, aim, and high-level objectives of this research are outlined.

Chapter 2: A critical review of the pertinent literature is presented, followed by the identified research gaps.

Chapter 3: The proposed research methodology and its subsequent phases and key steps are presented.

Chapter 4: The rationale of the used methods and tools and their fundamental theories are presented.

Chapter 5: The reference system and investigated case studies of different phases of the proposed methodology are presented.

Chapter 6: The derived results and discussion are presented.

Chapter 7: The final remarks and conclusions of this research are presented. Finally, the achievement of the aim and objectives are presented, including the outlook for future work.

Chapter 2

Literature Review

2.1 Safety Assessment

2.1.1 Design & Operation

Pertinent studies in the literature primarily focused on identifying preliminary hazards associated with MASS design and operation to support risk-informed design during its early development phases. Rodseth et al. [67] and Rodseth et al. [68] conducted hazard identification and risk assessment on a MASS concept design considering functions and interaction between the main modules, such as the MASS, target ships (TSs), and remote control centre (RCC), to simplify the operational and technical complexity. The feasibility of an unmanned ship concept was highlighted, where obstacle detection, path planning, and collision avoidance were identified as the most complex operations. Wrobel et al. [69] carried out risk analysis associated with MASSs based on experts opinion to systematically assess hazards from their design and operation and quantify their consequences. The critical interdependence between MASS systems was noted with the potential of leading to catastrophic consequences as a result of failure propagation, underlining the importance of accurately mapping the dependency between the systems.

Utne et al. [70] identified risks related to MASS systems of different degrees of autonomy to establish risk management strategies. The need for risk analysis and systematic acquisition of data throughout the whole life cycle of the system and the need for risk models that can provide online decision support proactively and reactively

for safer operation were highlighted. Thieme et al. [71] conducted preliminary hazard analysis to identify hazards during the design of a small autonomous passenger ship. Proposed risk-reducing measures were associated with software failure, communication system failure, traffic, passengers, monitoring and weather conditions and highlighted the limitations related to conventional risk analysis methods, lack of data, and lack of regulations, such as safety level. Fan et al. [72] identified risk influencing factors using expert opinion to measure the risk level of a remotely controlled MASS during different operating phases, such as voyage planning, berthing and unberthing, port approaching and departing, and open sea navigation. The open sea navigation operating phase was found to exhibit the most risk-influencing factors, mostly related to human factors. Chang et al. [73] used failure modes and effects analysis, evidential reasoning, and rule-based Bayesian network (BN) to identify major hazards related to MASS operation and quantify their risk using expert opinion. Major hazards contributing to the risk of MASS operation were related to interaction with manned vessels, obstacle detection, cyber-attacks, human error, and equipment failure.

Several studies investigated the control structure by qualitatively analysing the risk involved in MASS systems. Wrobel et al. [74] provided a safety control structure of a remotely controlled MASS using system-theoretic process analysis (STPA) to provide risk-reducing measures and assess their effectiveness during the design phase. Enhancing the reliability of vessel's technical equipment was highlighted as the most effective measure in reducing violation of safety constraints, especially when focusing on reducing the likelihood of inadequate control during remote control. Wrobel et al. [75] conducted uncertainty assessment of an STPA-based MASS design. Despite the lack of operating system and data, it was concluded that the uncertainties are expected to be manageable except for the mitigation measures concerning the software. More specifically, Wrobel et al. [76] underlined the greater influence of software on the safety performance of MASSs, which is expected to be integrated with every component, and the highest uncertainty pertaining to its feasibility. Utne et al. [77] identified and analysed hazards using STPA and integrated a BN-based online risk model into the mission layer of the control hierarchy to enable supervisory risk control of autonomous systems capable of risk management. Approaches towards feedback control based on real-time estimation of the current risk level and optimisation based on predicted future risk were suggested.

2.1.2 Hazardous Event

Some studies investigated various hazardous events pertaining to MASS operation failure or accident events. Zhou et al. [78] used an STPA-based control structure of a remotely controlled MASS and used hierarchical Bayesian inference to quantify the adequacy of situation awareness. The probability of the remote operator losing adequate situation awareness was indicated to be higher than manned ships. Zhang et al. [79] used hybrid causal logic to conduct preliminary hazard analysis and calculate the accident probability by developing contact scenarios of a remotely controlled MASS using event sequence diagram and used fault tree analysis (FTA) and BN to quantify risk influencing factors of mechanical components, human, and MASS. The importance of redundant design, such as to enhance the situation awareness of remote operators or reduce the failure probability of power and propulsion systems, was highlighted.

Wrobel et al. [80] qualitatively analysed the hazards of reported conventional accidents by conducting what-if analysis and human factors analysis to assess the impact on the occurrence and consequences on reported conventional accidents should the ships were MASSs. The results indicate that the occurrence of navigational accidents, such as collision and grounding, can be decreased with the operation of MASSs with an increase in the accident consequences compared to conventional ones. Wu et al. [52] assessed the collision risk by investigating MASSs and manned vessels collision scenarios using hybrid causal logic to qualitatively and quantitatively investigate the occurrence of collision accidents. It was found that the occurrence of collision accidents can be decreased even without communication between the ships.

Chou et al. [81] quantified the navigational risk of MASS by integrating experts opinion on MASS and actual conventional accident data. The probability of mechanical malfunction was found to be highest during navigation at open seas, whereas the probability of collision was found to be highest at ports. Guo et al. [82] quantitatively assessed the collision risk using a BN-based model for a MASS ferry and manned vessels operating in a canal. The probability of losing navigational control of the MASS, such as due to intervention failure of a remote operator, failure of decision-making system, failure of obstacle detection, and cyber-attack, constituted the most followed by the collision of MASS with manned vessels.

2.1.3 Risk Influencing Factor

A few studies considered the human factor during the safety assessment of MASS design and operation. Thieme et al. [83] used BN to assess the human-autonomy performance of autonomous underwater vehicles to improve their design and operation towards mission success. The inclusion of well-trained human operators, improvement of autonomous functions reliability, and situation awareness were found to be the most critical to the probability of mission success. Allal et al. [84] quantified the probability of human error using human reliability analysis, event tree analysis, and technique for human error rate prediction to identify vulnerabilities of human error during task procedures of MASS in port. The importance of early error detection at the early phase of design or operation through the implementation of human error recovery mechanisms and barriers was concluded. Ramos et al. [85] conducted task analysis of human remote operator during the interaction with collision avoidance system based on hierarchical task analysis and cognitive model to investigate the human-machine interaction. It underlined the human element as the safety barrier for successful collision avoidance and provided decision support for human-integrated MASS design.

Only a limited number of studies focused on investigating the risk pertaining to the failure of MASS machinery and cyber-security. Eriksen et al. [54] assessed the reliability and maintenance issues of MASSs machinery by conducting an improved reliability-centred maintenance method. Despite the not significantly different probability of machinery failure between manned and unmanned operations, the main challenge of unmanned operation was identified to be the inability to conduct corrective maintenance onboard. Tusher et al. [86] assessed the cyber-security risk of MASSs using expert opinion and Bayesian best-worst method to rank the vulnerability of equipment and systems against cyber threats. Navigational systems were found to be the most vulnerable to cyber attacks, such as global navigation satellite system (GNSS), electronic chart display and information system (ECDIS), and communication devices on RCC, with the propulsion system to be the least, such as engine control.

2.1.4 Collision Risk Indices

Numerous studies have investigated the assessment of collision risk by proposing various metrics, known as collision risk indices (CRIs), that assist the decision making for the collision avoidance by either triggering a collision alarm or initiating collision avoidance [87]. Bukhari et al. [88] used the distance to the closest point of approach (DCPA), time to the closest point of approach (TCPA), and bearing to automatically assess the collision risk using vehicle traffic service radar measurements in real time. The increased accuracy of collision risk assessment even in multi-ship scenarios was verified compared to classical methods that consider only ship-to-ship scenarios. Wang et al. [89] used a dynamic DCPA and TCPA based on the ship manoeuvrability to calculate a dynamic collision risk for close-quarters scenarios. The accuracy of the proposed metric for ship-to-ship encounter scenarios was verified compared to when the ship manoeuvrability is neglected.

Zhang et al. [90] proposed a probabilistic ship domain to divide the domain into forbidden, risk, and safe areas derived from big automatic identification system (AIS) data. The advantage of capturing diverse navigational behaviours was noted, especially for different navigating speeds and operating areas. Yoo et al. [91] assessed the collision risk not based on the violation of ship domain but by moving the ship domain at the closest point of approach (CPA) position. Simulation results suggested better risk assessment considering the effect of collision avoidance action on the risk, such as course alteration and speed changes. Zheng et al. [92] used the margin between ship domains and ship states to calculate the probability of collision based on support vector machine method. The ability to maintain a certain risk level, due to consideration of current and future ship states for continuous risk evaluation was noted. Li et al. [93] proposed an elliptical ship domain that dynamically changes based on ship speed and manoeuvrability. Higher accuracy of identifying collision risk and better safety were demonstrated with a scaling ship domain. Similarly, Deng et al. [94] proposed a dynamic ship domain parameterised according to the ship parameters, manoeuvrability, sailing speed, relative bearing, and COLREG. The effectiveness of this proposed approach to more accurately assess the collision risk was verified, while achieving shorter trajectories.

Huang et al. [87] proposed a time-varying CRI that assesses not only the collision

risk but also the difficulty of evasive manoeuvre based on its manoeuvrability to identify whether a collision avoidance is feasible or not. The monotonically increasing collision risk with the introduction of more ships and underestimation of collision risk when ship manoeuvrability is not taken into consideration were observed. Woerner et al. [95] defined metrics that quantify the subjective aspects of COLREG to standardise the evaluation of MASSs performance. The effectiveness of the proposed approach to detect COLREG non-compliance and adjust its collision avoidance strategies was noted. Hu et al. [96] proposed a CRI that incorporates COLREG and good seamanship and assessed the collision risk using fuzzy logic (FL) to provide early warning for multi-ship scenarios. Results demonstrated that real-time collision risk warnings can be provided even when different collision risk thresholds among the ships were used, compensating for the subjectivity of risk perception.

2.2 Decision-Making

2.2.1 Static Obstacles

Pertinent studies in the literature have investigated various collision avoidance and path-following strategies in different scenarios with static obstacles. Specifically, Xu et al. [97] employed modified artificial potential field (APF) and velocity obstacle (VO) in scenarios with single or multiple static obstacles to achieve coupled path following and collision avoidance control. The effectiveness of the approach to follow a predefined path, while avoiding collision, was demonstrated both virtually and experimentally. Chen et al. [98] used a hybrid approach of fast marching square and VO to generate optimal paths based on the parameters of collision risk and path length in static obstacles. Simulation results demonstrated the ability to avoid high-risk areas, while minimising the total length. Meyer et al. [99] used proximal policy optimisation (PPO) to realise collision avoidance in complex static environment with obstacles obscuring its predefined path. The capability of adjusting the guidance strategy towards path-adherence or collision avoidance was demonstrated with great success rate above 90%.

2.2.2 Dynamic Obstacles

A few studies investigated collision avoidance in multi-ship scenarios under coordinated frameworks, where interacting ships share the same decision-making objectives. Zhao et al. [100] used clipped PPO and classified TSs based on the four regions defined by COLREG, while considering the nearest ship in each region, to achieve path following and COLREG-compliant collision avoidance. The effectiveness of the proposed methodology was verified in ship-to-ship and multi-ship scenarios. Ahmed et al. [101] assessed the collision risk using FL and expert opinion based on DCPA and TCPA and considered ship dynamics to predict the ship motion more accurately. The collision risk was tuned based on ship size, speed, and number of ships, and the effectiveness was demonstrated in a multi-ship encounter of up to five vessels. Hu et al. [96] assessed the collision risk using FL based on COLREG and good seamanship, such as early and timely actions. The effectiveness was verified even when the collision risk thresholds were different for each ship accounting for the subjectivity of perceived collision risk. Cho et al. [102] employed a fast probabilistic VO (FPVO), where prediction uncertainty of the velocity and relative bearing and relative course were considered to resolve a multi-ship encounter situation. Monte-Carlo simulations were conducted and the accuracy and computational efficiency of FPVO compared to traditional probabilistic VO was verified.

Other studies investigated more challenging collision avoidance approaches in multi-ship scenarios under uncoordinated frameworks, where interacting ships make decisions independent of each other. For instance, Gao et al. [103] employed particle swarm optimisation (PSO) and dynamic window (DW) in scenarios with a single dynamic obstacle, while complying with the COLREG. The compliance to ship-to-ship scenarios under head-on, crossing, and overtaking situations was verified both virtually and experimentally. Johansen et al. [104] employed model predictive control (MPC) to select the optimal COLREG-compliant control behaviour amidst single to multi-ship scenarios, where the collision risk based on finite set of alternative control behaviours was assessed on a finite prediction horizon. The uncertainty of the predicted obstacles behaviour was accounted for by generating multiple trajectory predictions of the obstacle and the robustness of the controller was verified even amidst obstacles with random motion. Shaobo et al. [105] used a modified VO

and conducted multistage optimisation to include various constraints due to ship manoeuvrability, COLREG, course maintenance, and good seamanship in multi-ship scenarios. The effectiveness of the approach to handle dynamic behaviours of the TS during the collision avoidance process was demonstrated.

2.2.3 Static & Dynamic Obstacles

Some studies investigated collision avoidance in mixed scenarios consisting of both static and dynamic obstacles. In particular, Serigstad et al. [106] employed hybrid DW and rapidly exploring random tree to generate time-parameterised trajectories. Simulation results demonstrated the ability to generate trajectories, while avoiding local minima and tracking the global path in real-time. Lyu et al. [107] employed hybrid APF to achieve path planning in restricted waters with dynamic obstacles. The effectiveness of the approach to generate deterministic collision-free and COLREG-compliant paths in real time was demonstrated. Similarly, Lyu et al. [108] used a modified APF, where COLREG-compliant evasive manoeuvres in multi-ship scenarios regardless of the number of obstacles and random course changes of the TSs were noted, accounting for the uncertainty of the TSs behaviour. Zhang et al. [109] used a modified APF and modified VO considering CPA, COLREG, and good seamanship to generate global and local paths. The ability of the local path planning to generate COLREG-compliant paths, while considering the ship manoeuvrability, was noted. Wang et al. [110] used a deep Q network (DQN) to achieve collision avoidance and COLREG compliance in static or dynamic scenarios. The effectiveness of the approach to conduct evasive manoeuvres amidst static obstacles and COLREG compliance and good seamanship amidst dynamic obstacles were verified.

2.2.4 Extreme Scenarios

A limited number of studies investigated the collision avoidance and path planning problem in more extreme scenarios. Specifically, Zhang et al. [111] investigated highly critical multi-ship scenarios, where the give-way vessel violated the COLREG. It was found that the COLREG violation of a single vessel greatly exacerbates the difficulty of COLREG compliance for the other vessels, such as by crossing from

the starboard side of other ships instead from port side or letting the give-way vessel cross from ahead of a stand-on vessel. Woerner et al. [112] quantified the compliance of a MASS to COLREG, while human-operated vessels were used to violate the navigational rules. Simulation results indicated that MASSs were capable of completing their mission goals, while complying with the COLREG, despite human efforts to violate the rules. Blindheim et al. [113] used MPC in scenarios with multiple static obstacles, considering dynamic risk pertaining to emergency situations, such as impaired thrusters, total blackout, or strong winds. The effectiveness of the approach to generate trajectories below of certain risk threshold in all of these scenarios was demonstrated.

2.2.5 Environmental Disturbances

Other studies considered environmental disturbances to account for more realistic scenarios. Particularly, Abdelaal et al. [114] employed nonlinear MPC for trajectory tracking, collision avoidance, and COLREG-compliance, while compensating for sideslip angle and constant or varying environmental disturbances, and used a nonlinear disturbance observer to estimate these disturbances. Robustness of the controller under various disturbances was verified, while maintaining minimum tracking error. Cheng et al. [115] used DQN in scenarios with multiple static obstacles and unknown environmental disturbances. The ability of the proposed approach to make decisions based on the current observations was noted without prior knowledge of the environmental disturbances states. Zhao et al. [116] used clipped PPO and considered environmental forces, such as wind, current, and waves, in the OS manoeuvring model to achieve path following, collision avoidance, and COLREG compliance under unknown environmental disturbances. Simulation results demonstrated COLREG-compliant collision avoidance, while following the predefined path, and derived better results compared to a traditional proportional-integral-derivative controller. Zheng et al. [117] used soft actor-critic to develop a controller that actively estimates and compensates for wind and wave disturbances during path following. The stability and robustness of the controller during straight and circular path following were verified compared to traditional linear active disturbance rejection controllers.

2.2.6 Situation Awareness

Most of the pertinent studies considered situation awareness of the navigating scenarios by assuming a prior knowledge of the encountered obstacles, such as using electronic navigational charts for static obstacles [118] and AIS data for dynamic obstacles [119]. Only a limited number of studies considered onboard sensors to account for more realistic data acquisition used in situation awareness. For instance, Zhou et al. [120], Meyer et al. [99], and Heiberg et al. [121] used general range finder sensors with multiple beams to measure the distances and relative angles to obstacles. Kim et al. [122], Gonzalez et al. [123], and Villa et al. [124] used light detection and rangings (LIDARs) to generate point clouds or clusters of the surrounding environment and measure the positions, distances, and relative angles to obstacles. Wang et al. [125] used radio detection and ranging (RADAR) to calculate the distance to the closest point of approach and the time to the closest point of approach. Song et al. [126] used automatic identification system for dynamic obstacles data. Peng et al. [127] used LIDAR and sound navigation and ranging (SONAR) to detect surface and underwater obstacles, respectively. Han et al. [128], Han et al. [129], and Kim et al. [130] compensated the noisy data using filtering techniques, such as extended Kalman filter, for perception sensors, such as electro-optical and infrared camera, RADAR, and LIDAR.

2.2.7 Actuators Control

Some studies considered the control output actuators during the collision avoidance and path following of MASSs. Specifically, Johansen et al. [104] used MPC to control the steering and propulsion system. Optimal rudder angle and speed commands were generated as set points to be achieved by an autopilot. Similarly, Ahmed et al. [101] used FL to generate the speed and heading command as set points for a conventional proportional–derivative (PD) controller. Kim et al. [122] used a PD controller to control the thrusters output and achieve the design speed and heading. Hu et al. [96] deterministically set the desired speed and course change based on the real-time CRI value. Zhao et al. [100] used clipped PPO to directly generate rudder angle output in real time based on the states received during collision avoidance scenarios. Similarly,

Martinsen et al. [131] used deep deterministic policy gradient (DDPG) to control the rudder angle during path following of a MASS. The effectiveness of addressing noisy rudder angle output by tuning the control objectives and steady-state error during course maintenance was presented.

2.3 Research Gaps

Critical review of the pertinent literature highlights the following research gaps.

1. Studies on safety assessment pertaining to the design and operation of MASSs remained on only high-level abstraction. However, scant research has been conducted for its safety-critical autonomous systems, such as the collision avoidance system at the component level, and quantitative risk analysis to support the risk-informed design of next-generation CAS has not been reported. How to design CAS for MASSs that will assure the safe collision avoidance amidst other MASSs and conventional ships compliant to the IMO instruments is missing.
2. Studies on CRIs have investigated only external factors pertaining to geometric parameters and environmental disturbances. The identification of internal factors, such as system failure, influencing the collision risk has not been addressed. How internal CRIs can be effectively incorporated with external CRIs, such as DCPA, TCPA, and ship domain, for a holistic collision risk assessment and safe decision-making is an open challenge.
3. Studies on CRIs have proposed various risk-influencing factors specific to the investigated scenarios. Despite some efforts to increase the accuracy of collision risk assessment and verify their generalisation capabilities, a single CRI that can accurately quantify the collision risk in any collision scenario has not been addressed. A universal CRI and collision risk threshold that can be applied not only to the investigated scenarios, but to different scenarios, any number of ships and types, are an open question.
4. Studies on acquiring situation awareness based on onboard perception sensors have considered only idealistic measurements or filtered measurements using

various filtering techniques. The effect of unfiltered sensor measurements during safety-critical operations, such as collision avoidance, has not been investigated. How to increase the robustness when noisy measurements are fed into the decision-making system remains open.

5. Studies on conducting collision avoidance amidst mixed environments address the static and dynamic obstacles by treating them equally or by relying on prior knowledge of their classification. However, conducting different evasive manoeuvres based on different classifications of the detected obstacles has not been tackled. How to classify obstacles as static or dynamic based on local information without prior information and external sources remains under-investigated.
6. Studies on reactive collision avoidance consider onboard perception sensors to detect collision-inducing obstacles. However, the relation between the detecting range and manoeuvrability of the own ship (OS) has not been reported. How to conduct safe reactive collision avoidance when the detecting range is critically limited compared to its manoeuvrability has not been addressed.
7. Studies on controlling the actuators have either generated the desired speed and heading achieved by conventional autopilots or controlled only the rudder angle of the steering system in real time with constant propeller revolution. However, directly mapping the observed states from the collision scenarios to the coupled control of the steering and propulsion systems in real time has not been reported. How to effectively control both the speed and heading for full-scale and underactuated vessels is a challenge to be addressed.
8. Studies on decision-making pertaining to the collision avoidance and path following of MASSs have reported the effectiveness of the proposed approaches in meeting the respective decision-making objectives. However, decision-making that exceeds the prior set decision-making objectives, such as sophisticated decision-making with risk awareness, balancing safety over efficiency, and alternative control strategies, is under-reported. How to develop decision-making systems that learn and propose more intelligent and alternative solutions is under-investigated.
9. Studies on decision-making for MASSs have evaluated their performance only

between other algorithms suitable for autonomous systems. Comparative assessment of the decision-making capabilities between the autonomous system and human operator has not been reported. The merits and downfalls of autonomous system's decision-making has only been speculated qualitatively and in which scenarios human operators outperform the autonomous systems to systematically train autonomous systems, realise human-autonomous systems collaboration, or transfer the responsibility to human operators remain unanswered.

10. Studies on decision-making for MASSs have evaluated their performance only via certain CRIs and for a certain number of scenarios. However, this raises the question of their robustness and sensitivity in other circumstances beyond the reported scenarios. Definition of robustness metrics based on operation requirements, the investigation of a whole spectrum of scenarios until a set operation requirements are violated, and sensitivity to certain collision risk influencing factors, need to be reported to evaluate the whole robustness spectrum of decision-making.
11. Studies on collision avoidance in multi-ship scenarios consider COLREG compliance to a certain degree. However, COLREG is limited only to ship-to-ship scenarios, especially considering conventional ships and abstract nuances for human operators. How to address this challenge by investigating more detailed or new regulations to capture multi-ship scenarios for both conventional ships and MASSs remains a challenge.
12. Studies on investigating extreme scenarios have put some effort into addressing more challenging scenarios, such as COLREG violation, environmental disturbances, and uncertainty of the TSs behaviour. However, other critical scenarios, such as safe collision avoidance and path following during cyber-attack, piracy, or extreme weather conditions, have not been reported yet. The investigation of the unknown-unknowns emerging from unpredictable scenarios remains a challenge.

Chapter 3

Research Methodology

A research methodology is proposed to achieve the aim of this research by addressing some of the identified research gaps. Specifically, the research gaps 1, 2, 4, 5, 6, 7, 8, and 10 are addressed, resulting in low-level objectives as follows.

1. Analyse the risk pertaining to the CAS at the component level to derive a risk-informed design that is compliant with the pertinent IMO instruments and optimal from risk and cost-benefit perspectives (*Research gap 1*).
2. Identify internal CRIs from risk analysis of the CAS and incorporate them into external CRIs (*Research gap 2*).
3. Enhance the robustness of decision-making for the reactive collision avoidance of a MASS against noisy perception sensor measurements (*Research gap 4*).
4. Classify the obstacles into static or dynamic in real-time based on raw perception sensor measurements acquired onboard without prior information (*Research gap 5*).
5. Enhance the robustness of decision-making for the reactive collision avoidance of a MASS even when the detecting range of a perception sensor is critically limited and comparable to its manoeuvrability (*Research gap 6*).
6. Control the rudder and propeller concurrently based on end-to-end decision-making approach (*Research gap 7*).
7. Enhance the sophisticated decision-making capable of balancing safety over efficiency and propose alternative control strategies (*Research gap 8*).

8. Evaluate the decision-making by proposing appropriate robustness metrics that quantify their performance in a diverse range of scenarios and investigate its sensitivity to collision risk influencing factors (*Research gap 10*).

Considering the above low-level objectives, the research methodology is formulated into five distinct phases, as presented in Figure 3.1. The rationale, assumptions, and subsequent steps of each phase are presented in the following Sections 3.1–3.5.

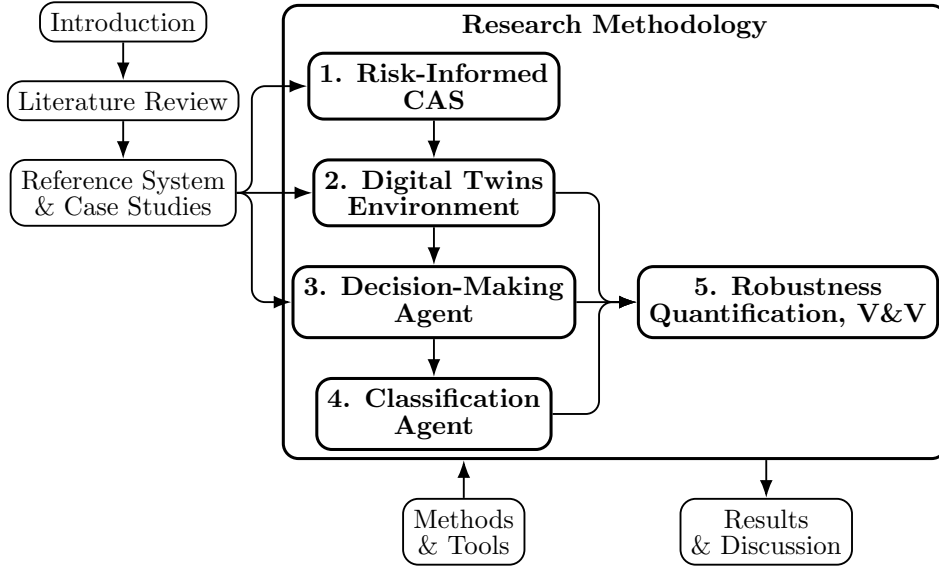


Figure 3.1 Proposed research methodology and its phases within the conducted research.

3.1 Risk-Informed Collision Avoidance System

In this phase, a risk-informed CAS is designed to address the low-level research objectives 1 and 2. The phase is analysed into its subsequent steps, as presented in Figure 3.2. A description of each subsequent step and its rationale are presented as follows.

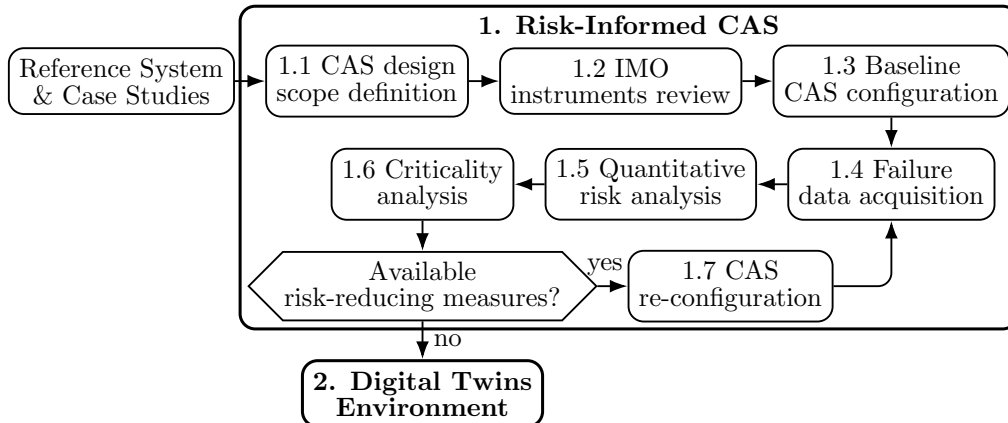


Figure 3.2 Subsequent steps of the first phase.

Step 1.1 CAS design scope definition

In step 1.1, the design scope of the CAS is defined to support the design rationale and pertinent requirements, such as the expected degree of autonomy, mission profile, operating conditions, etc. Such requirements depend on the investigated reference system and case studies.

Step 1.2 IMO instruments review

In step 1.2, the IMO instruments pertinent to collision avoidance, systems, and components are reviewed, such as the COLREG and International Convention for the Safety of Life at Sea (SOLAS), to brainstorm the functional and system requirements of the CAS. Despite the lack of IMO instruments specific to MASSs, it is assumed that the first generation MASSs to be employed will comply to the current regulations with little amendments on the conventional regulations, as proposed by the IMO's MSC during its regulatory scoping exercise [12].

Step 1.3 Baseline CAS configuration

In step 1.3, a baseline CAS configuration that complies to the identified functional and system requirements is proposed at the component level. Components from the currently available technology are identified to mitigate the introduction of inevitable uncertainties, such as pertaining to their expected failure modes [79]. Also, the lowest level of abstraction for the CAS design is assumed to be the component level [64], which is treated as a “black-box” level considering that no further details can be obtained due to the low chance of redesign.

Step 1.4 Failure data acquisition

In step 1.4, failure data of the CAS components are acquired, such as the probability of failure or failure rate [53], by referring to reliability data and pertinent literature. Failure data is assumed to be the same for conventional components [79], whereas, failure data for unknown components, such as AI software [58], is speculated according to the expert opinion.

Step 1.5 Quantitative risk analysis

In step 1.5, quantitative risk analysis is conducted to identify the risk involved in the CAS configuration, such as weak design points and critical components, which

are expressed via internal risk metrics, such as probability of failure and importance measures. Risk analysis refers to the systematic study that is carried out to describe an undesired event and identify its causes, likelihoods, and consequences [58]. Quantitative risk analysis is a sub-process of risk analysis [132] that focuses on the expression of the risk in probabilistic terms [133]. Quantitative risk analysis is particularly pivotal for safety-critical systems, such as CAS whose failure can lead to major hazards, to better support the decision-making pertaining to their design and operation [58]. For a safety-critical system such as the CAS, where real data from its design and operation is lacking, the failure of the system is assumed to be sufficient enough to have catastrophic consequences, such as near-miss collision incident or even collision accident [74].

Step 1.6 Criticality analysis

In step 1.6, criticality analysis is conducted to identify the most critical internal risk metrics and effectively allocate available risk-reducing resources to the most critical vulnerabilities of the system [134].

Step 1.7 CAS re-configuration

In step 1.7, the CAS is re-configured based on the availability of risk-reducing measures on the most critical vulnerabilities identified during the criticality analysis, leading to the design iteration of steps 1.4–1.6. This design iteration can be terminated upon reducing the critical internal risk metrics derived from the quantitative risk analysis below a certain threshold. However, due to the lack of current regulations regarding such thresholds, the availability of risk-reducing measures assessed from commonly followed risk-reducing practices from a cost-benefit perspective is assumed to be sufficient [135]. Finally, when no further risk-reducing measures are available, the final risk-informed CAS design and its pertinent internal risk metrics are derived, such as probability of failure, importance measures, etc.

3.2 Digital Twins Environment

In this phase, digital twins are developed to address the low-level research objectives 2, 3, 4, 5, and 6. Digital twin stands for the accurate time-domain virtual representation

of the physical twin's full-scale reality [136]. Specifically, digital twin is a model represented by algorithms that mirror the most important components and behaviours of the physical system by generating similar outputs as the physical counterpart given the same inputs [137]. The development of digital twins is of paramount importance for the proactive safety verification of autonomous systems in safety-critical scenarios [138], enabling the generation of new information and collection of data without risking damage of a full-scale system, environmental pollution, and human life loss [139]. The whole digital twins environment framework consists of the real-time data collection from the physical twin, communication between the physical and digital twins, virtual simulation of the digital twin, and decision support or making pertaining to the physical twin [140]. However, considering the lack of full-scale physical implementation of MASSs, the scope of the digital twins environment is assumed to be limited to virtual simulations. The phase is analysed into its subsequent steps as presented in Figure 3.3. A description of each step and its rationale are presented as follows.

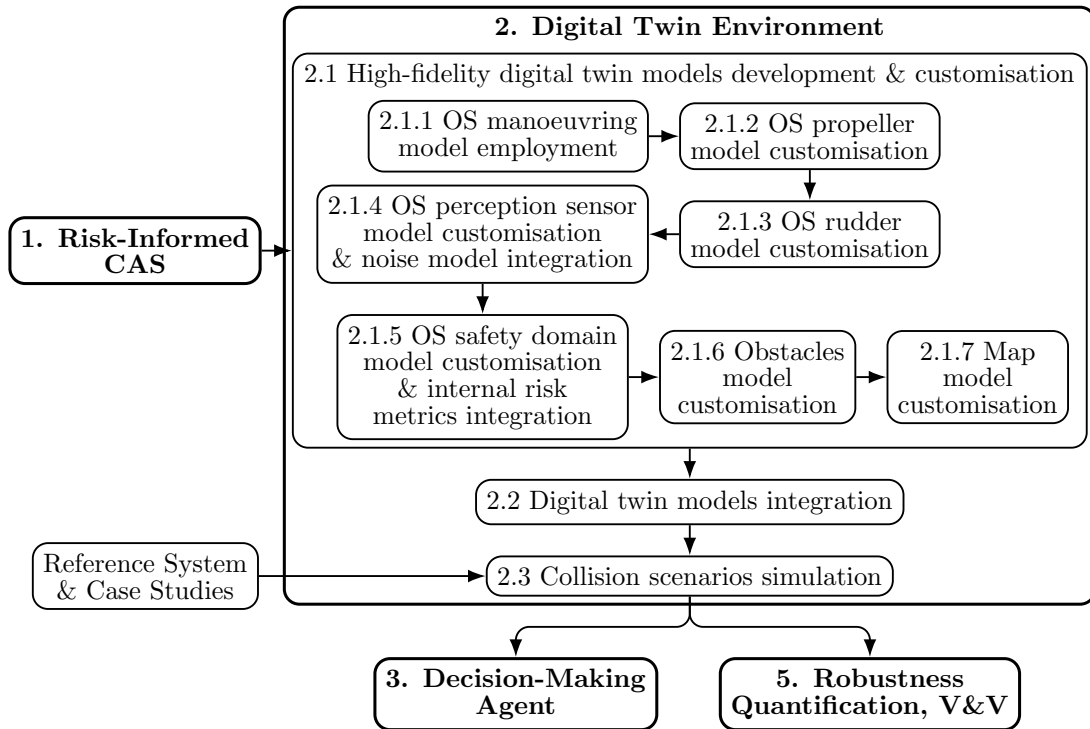


Figure 3.3 Subsequent steps of the second phase.

Step 2.1 High-fidelity digital twin models development & customisation

In step 2.1, high-fidelity digital twin models of the main components pertaining to the collision scenarios of a MASS are developed and customised, as presented in the subsequent steps. Trustworthiness of the digital twins, which refers to a

multidimensional and holistic property that measures the quality of a system [141], is evaluated from the perspective of their fidelity, such as the level of virtual simulations' accuracy.

Step 2.1.1 OS manoeuvring model employment

In step 2.1.1, the digital twin of the manoeuvring model is employed to simulate the manoeuvrability characteristics of the investigated vessel. Manoeuvrability refers to the ability of a ship to maintain or change its motion states under the operation of actuators [142].

Step 2.1.2 OS propeller model customisation

In step 2.1.2, the digital twin of the propeller model is customised to simulate its control dynamics, including the setting of its dynamic range, such as its maximum revolution and acceleration and deceleration rates.

Step 2.1.3 OS rudder model customisation

In step 2.1.3, the digital twin of the rudder model is customised to simulate its control dynamics, including the setting of its dynamic range, such as its maximum rudder angle and deflection rate.

Step 2.1.4 OS perception sensor model customisation & noise model integration

In step 2.1.4, the digital twin of the perception sensor model is customised based on the modelling of its measurement principle for the detection of obstacles. Perception sensor refers to an exteroceptive sensor that measures values originating outside of the controlled system to perceive the surrounding environment, in contrast to a localisation sensor that is proprioceptive and measures values within the system to localise it with respect to the perceived environment [143]. Customisation of the perception sensor model is associated with the setting of its resolution, dimensions, and frequency. In addition, a high-fidelity perception sensor digital twin needs to integrate sensor noise to simulate realistic measurements [144]. Thus, a noise model is integrated in the measurements of the perception sensor model considering its stochastic noise generation and noise level intensity.

Step 2.1.5 OS safety domain model customisation & internal risk metrics integration

In step 2.1.5, the digital twin of the ship domain model is customised to simulate the collision criteria. Specifically, ship domain refers to the safety margin around the OS to be kept free from obstacles [145], and its customisation is associated with the setting of its dimensions, shape, etc. Apart from the high-fidelity requirement of digital twins for trustworthy simulations, probabilistic simulations due to unknown-unknowns and system degradation also need to be considered [138]. Thus, a dynamic safety domain that adjusts its size based on the CAS probability of failure is developed.

Step 2.1.6 Obstacles model customisation

In step 2.1.6, the digital twin of the obstacles model is customised to simulate realistic surface obstacles that impose collision risk. Their customisation is pertaining to their size, shapes, and dynamics, such as static or moving.

Step 2.1.7 Map model customisation

In step 2.1.7, the digital twin of the map model is customised to simulate the navigational area of the OS. Map refers to the spatial representation of the environment [146] and its customisation is associated with the setting of its resolution and dimensions.

Step 2.2 Digital twin models integration

In step 2.2, the developed and customised digital twins are integrated into a common environment to provide a common virtual testing ground.

Step 2.3 Collision scenarios simulations

Finally, in step 2.3, high-fidelity simulations of highly critical collision scenarios are simulated based on the investigated case studies.

3.3 Decision-Making Agent

In this phase, a decision-making agent is trained to address the low-level research objectives 3, 5, 6, and 7. The phase is analysed into its subsequent steps, as presented

in Figure 3.4. A description of each subsequent step and its rationale are presented as follows.

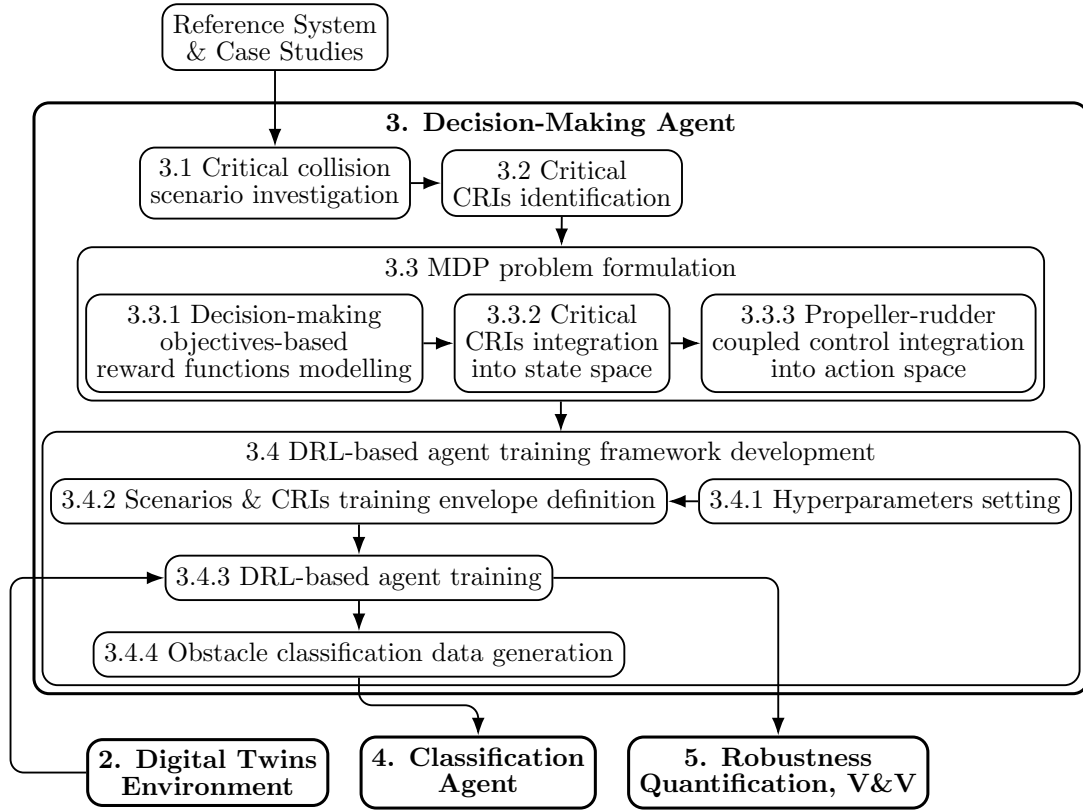


Figure 3.4 Subsequent steps of the third phase.

Step 3.1 Critical collision scenarios investigation

In step 3.1, critical collision scenarios are investigated based on case studies.

Step 3.2 Critical collision risk indices identification

In step 3.2, critical CRIs from the investigated critical collision scenarios are identified, such as relative distance and angle to obstacles, safety domain, etc.

Step 3.3 Markov decision process problem formulation

In step 3.3, the decision-making problem pertaining to the investigated critical collision scenarios are formulated as Markov decision processes (MDPs). Specifically, MDP is a mathematical framework for complex sequential decision-making problems under uncertainty [147]. In fact, many real-world decision-making problems can be modelled as MDPs due to their abstract and flexible frameworks [148]. The fundamental idea of this framework is to achieve a goal by learning from interactions, in which the learning decision-maker is known as the agent and everything else that interacts with it as the environment, such as the digital twins environment that

simulates the critical collision scenarios. The formulation of the decision-making problem as a MDP is pertaining to the identification of the reward functions, state space, and action space as presented in the following steps.

Step 3.3.1 Decision-making objectives-based reward functions modelling

In step 3.3.1, the reward functions are modelled according to the decision-making objectives such as path following, nominal navigation, actuator control, and collision avoidance objectives. The rewards that the agent learns to maximise are defined as reward functions [148].

Step 3.3.2 Critical collision risk indices integration into state space

In step 3.3.2, the prior identified critical CRIs are integrated into the state space. The states that the agent receives from the environment are identified as the set of variables related to the rewards, known as observations, which constitute the state space [149]. A low-dimensional state space that consists of a limited number of observations can lead to an incomplete understanding of the environment and sub-optimal decision-making, whereas a high-dimensional state space can exponentially increase the computational complexity and training time of the agent [150]. The integration of critical CRIs into the state space is pivotal for the agent's awareness of critical risk-related parameters during its decision-making.

Step 3.3.3 Propeller-rudder coupled control integration into action space

In step 3.3.3, the propeller and rudder control outputs are integrated into the action space to achieve the desired decision-making objectives by concurrently controlling their dynamics. The actions that the agent executes to affect the state of the environment and maximise the rewards are identified as the set of all possible actions that the actuator can take, which constitutes the action space [149].

Step 3.4 DRL-based agent training framework development

In step 3.4, a framework is developed for the training of a deep reinforcement learning (DRL)-based agent to make decisions over the formulated MDP problem. Recently, DRL-based agents have gained significant attention due to the major breakthroughs achieved in decision-making, by integrating the trial-and-error techniques of reinforcement learning and feature extraction capabilities of deep learning (DL) using

deep neural networks (DNNs) [151]. Specifically, DRL-based agents have surpassed previous limitations of addressing complex decision-making problems with high-dimensional state and action spaces [152] with significant end-to-end learning [153] at a human level [154, 155], whose application range from high-precision robotic arms to self-driving cars and more [156]. Thus, DRL-based agents are often preferred over other alternatives, such as dynamic programming, value iteration, evolutionary and heuristic algorithms [157, 158]. The training framework is developed as presented in the following steps.

Step 3.4.1 Hyperparameters setting

In step 3.4.1, the hyperparameters of the DRL-based agent are set up. The hyperparameters are the parameters of the DNNs set prior to the training of the agent, such as the architecture of the DNN, such as number of hidden layers and number of neurons, that directly impact its learning speed [159, 160] and whose settings can vary depending on the complexity and required accuracy of the decision making [161].

Step 3.4.2 Scenarios & CRIs training envelope definition

In step 3.4.2, the boundaries of the investigated scenarios and CRIs during the training of the agent is defined, which constitute the training envelope.

Step 3.4.3 DRL-based agent training

In step 3.4.3, the DRL-based agent is trained to optimise its decision-making within the defined training envelope. Specifically, a random training envelope is generated for each episode from uniformly distributed random numbers between predefined minimum and maximum values, where an episode stands for the sequence of timesteps of an episodic task from the beginning to the end [149].

Step 3.4.4 Obstacle classification data generation

In step 3.4.4, the data generated during the critical collision scenarios are acquired for obstacle classification, such as the perception sensor measurements. Finally, the trained decision-making agent is derived at the end of this phase.

3.4 Classification Agent

In this phase, a classification agent is trained to address the low-level research objective 4. Specifically, a framework is developed for the training of a DL-based agent to solve the obstacle classification problem based on the data acquired from the previous phase. Recently, DL-based agents have gained significant attention due to their generality, expressiveness, and flexibility in automatic feature engineering and end-to-end learning for previously challenging problems, such as natural language processing and image recognition using big data, thus replacing previous alternatives, such as linear regression, support vector machines, decision trees, etc. [156]. The phase is analysed into its subsequent steps, as presented in Figure 3.5. A description of each subsequent step and its rationale are presented as follows.

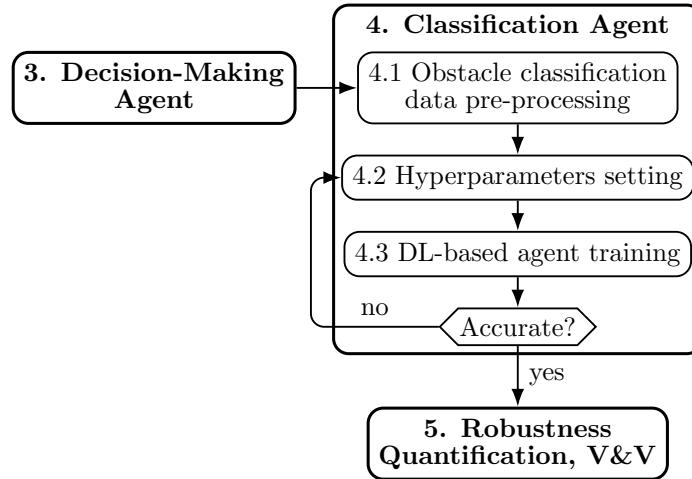


Figure 3.5 Subsequent steps of the fourth phase.

Step 4.1 Obstacle classification data pre-processing

In step 4.1, the acquired obstacle classification data is pre-processed, including the labelling of the raw data as static or dynamic and separation of the data for training and verification.

Step 4.2 Hyperparameters setting

In step 4.2, the hyperparameters of the DL-based agent are set up, including the architecture of the DNN, such as the number of hidden layers and number of neurons.

Step 4.3 DL-based agent training

In step 4.3, the DL-based agent is trained to optimise its classification accuracy within the defined training data. The accuracy of the agent is verified using the verification data, where steps 4.2 and 4.3 are repeated until the classification satisfies a certain accuracy. Finally, the trained classification agent is derived at the end of this phase.

3.5 Robustness Quantification, Verification & Validation

In this phase, the robustness of the decision-making agent is quantified, verified and validated (V&V) to address the low-level research objectives 3, 5, and 8. The phase is analysed into its subsequent steps, as presented in Figure 3.6. A description of each subsequent step and its rationale are presented as follows.

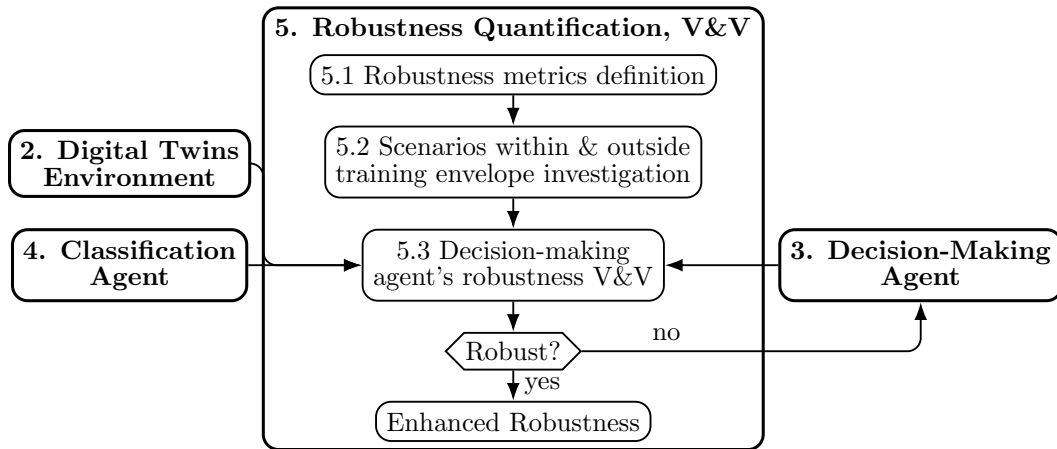


Figure 3.6 Subsequent steps of the fifth phase.

Step 5.1 Robustness metrics definition

In step 5.1, appropriate robustness metrics are defined based on the operation requirements, such as path following requirements, safe distance from obstacles, and COLREG compliance. Specifically, robustness metrics are defined with a set threshold, in order to provide a binary assessment of system's robustness state based on the compliance or violation of the threshold. In addition, it enables the assessment of the system's robustness degree by quantifying the margins towards violating the threshold.

Step 5.2 Scenarios within & outside training envelope investigation

In step 5.2, the scenarios within and outside the trained envelope to apply the robustness metrics are investigated.

Step 5.3 Decision-making agent's robustness verification and validation

In step 5.3, the decision-making agent's robustness is V&V in the investigated scenarios. Specifically, compliance with the defined robustness thresholds is investigated within and outside the training envelope. The verification is conducted within the developed digital twins environment. The validation is conducted in experimental settings. If the threshold requirements are not satisfied, then training of the decision-making is repeated in the third phase, leading to the hyperparameters setting optimisation. Finally, a decision-making agent with enhanced robustness against critical collision scenarios is derived addressing the aim of this research. A detailed flowchart of the proposed research methodology is presented in Figure 3.7.

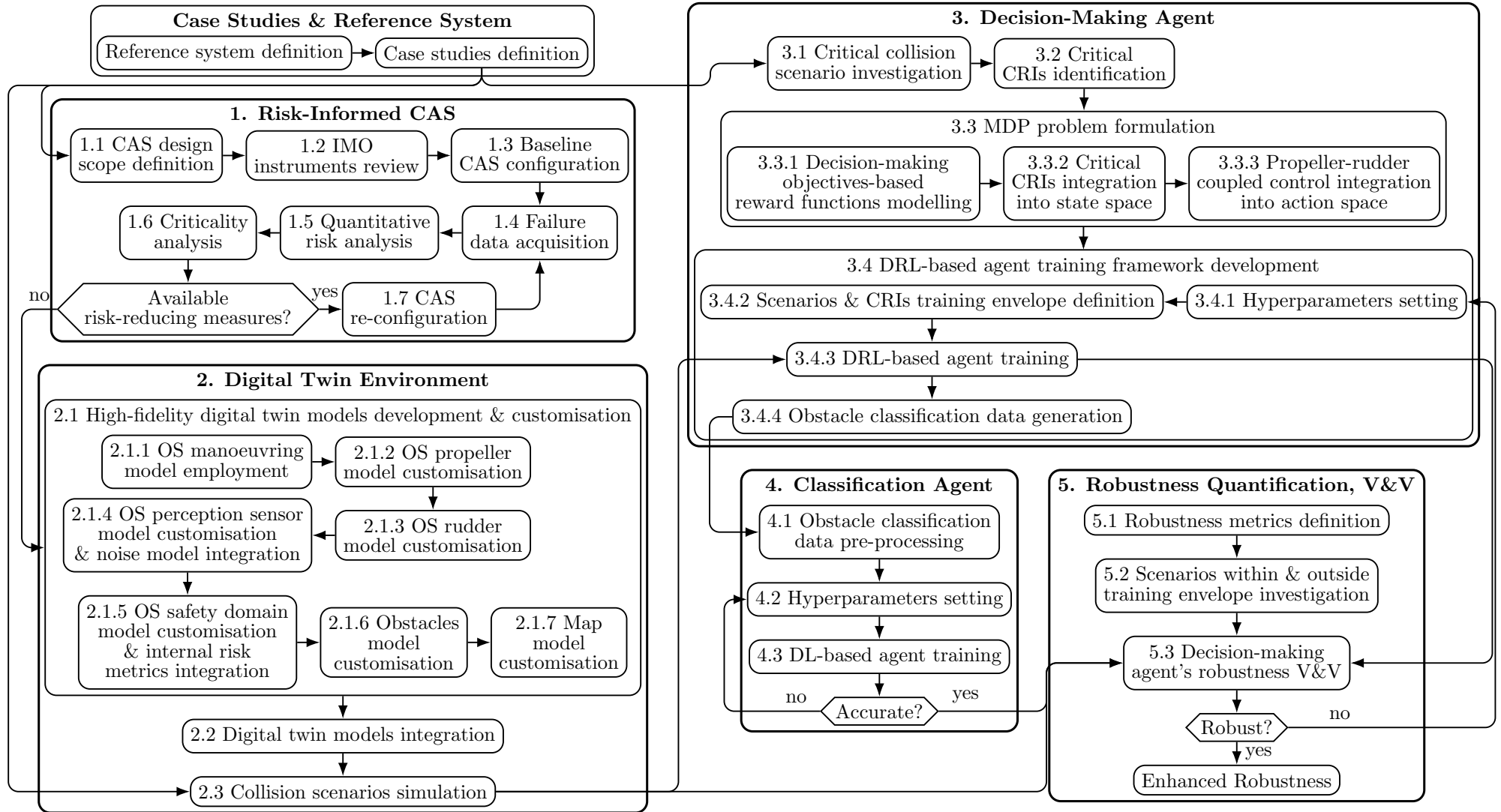


Figure 3.7 Flowchart of the proposed research methodology.

Chapter 4

Methods & Tools

4.1 Quantitative Risk Analysis

4.1.1 Fault Tree Analysis

FTA is one of the most extensively used methods in risk analysis and is extensively used to identify critical events and weak design points leading to the occurrence of the hazardous event and recommend risk-reducing measures related to system components, structure, and barriers [58]. FTA was first introduced in 1962 to investigate the reliability of a missile launch control system [162]. Up to date, it has been an essential method whose application spans across a wide range of safety-critical systems, including nuclear power plants [163], chemical process [164], spacecrafts [165], commercial aircraft systems [166], automobiles [167], cyber-security systems [168], and collision risk alarm systems [52].

The major advantage of FTA compared to other methods is its compatibility with complex systems of intertwined hardware and software interactions, particularly for new systems where design information is incomplete [169], as presented in Table 4.1. Some of its limitation, such as inability to capture time-related dependencies [170] and analyse dynamic systems of non-binary state [58], can be compensated using some of its variations, such as dynamic FTA [171], repairable FTA [172], and fuzzy FTA [173]. However, since the developed baseline CAS configuration of this study considers a straightforward decomposition into its components the use of a static FTA is considered to be adequate as a decision-support method pertaining to its

design. When it comes to static FTA as a method to identify critical internal CRIs during its operation, the relatively short collision avoidance operation ranging to a few minutes is assumed to be sufficient without significant degradation.

Table 4.1 Comparison of quantitative risk analysis methods.

Method	Main advantages [58, 174]	Main limitations [58, 174]
FTA	• Most commonly used for causal and frequency analysis. • Available international standard and well-documented method. • Suitable for a wide range of applications. • Available for both qualitative and quantitative analysis. • Suitable for large and complicated systems with ample degree of redundancy.	• Not suitable for dynamic systems. • Not suitable for systems with complicated maintenance. • Too rigid due to consideration of binary states and Boolean logic.
BN	• Good alternative to FTA for causal and frequency analysis. • More flexible than FTA.	• More complicated than FTA. • Quantification is more time-consuming. • Not available international standard.
Markov methods	• Suitable for small, complicated, and dynamic systems. • Good alternative to FTA for frequency analysis. • Available international standard and well documented.	• Not suitable for initial causal analysis.

FTA uses graphical symbols and Boolean logic to model the occurrence of a hazardous event and combination of causes in a deductive manner, known as the fault tree (FT) diagram [175, 176]. The FT diagram is modelled using logic gates based on Boolean logic to reflect causal relationship [58], as presented in Table 4.2. To perform FTA, first, a hazardous event, referred as the top event (TE) [169], is defined and is systematically decomposed into its subsequent causal events, known as the intermediate events (IEs) [177]. Similarly, the IEs are decomposed into their subsequent events until the lowest level of causal events is reached, known as the basic events (BEs) or root nodes [58], which represent simpler forms of initiating failures, such as component failures [175].

It is worth noting that every FT diagram is single event-oriented, meaning that it represents only a specific TE [58]. Also, every FT diagram is deterministic, meaning that knowledge of all BEs' states, the states of the TE and IEs are known using

synthesis [58]. The main assumptions of this method are as follows.

- Events are statistically independent [58].
- Failure rates are constant [58].
- Any failure event is binary and no degradation of the components is taken into account [164].
- The system is assumed to be capable of performing its intended task when all components are not in a failed state [164].

Table 4.2 FT diagram logic gates.

Gate name		Description
And-gate		The output event occurs if all input events occur.
Or-gate		The output event occurs if at least one of the input events occurs.
Vote-gate		The output event occurs if k or more of the input events occur.
Transfer-gate		Indicates a transfer continuation to a subsequent fault tree.
Event		Indicates an event, such as the top event.
Basic event		A basic initiating fault.

When the FT diagram is known, input data for the BEs' probabilities are acquired in order to determine various fault properties [58]. Typically, stochastic measures based on reliability data provided by generic and company-specific databases are acquired, which are of particular use when historical record of the same accident or near accident is now available [164]. The most commonly used stochastic measures are the reliability, availability, mean time to first failure, mean time to failure, mean time between failure (MTBF), mean time to repair, and expected number of failures [170].

Given the FT diagram and input data for the BEs, the main quantitative fault property derived from FTA is the TE probability [164]. Probability is dimensionless, ranging from 0 to 1, used to describe the likelihood of an event occurring during a specified time interval [164]. The boolean and probability expressions of a TE with an and-gate and a TE with an or-gate are presented in Equations 4.1–4.2 and Equations 4.3–4.4, respectively.

$$\text{TE}(t) = \text{BE}_1(t) \cap \text{BE}_2(t) \cap \cdots \cap \text{BE}_n(t) \quad (4.1)$$

$$\begin{aligned}
Q_{TE}(t) &= Pr[BE_1(t) \cap BE_2(t) \cap \dots \cap BE_n(t)] \\
&= Pr[BE_1(t)]Pr[BE_2(t)] \dots Pr[BE_n(t)] \\
&= q_1(t)q_2(t) \dots q_n(t) \\
&= \prod_{i=1}^n q_i(t)
\end{aligned} \tag{4.2}$$

$$TE(t) = BE_1(t) \cup BE_2(t) \cup \dots \cup BE_n(t) \tag{4.3}$$

$$\begin{aligned}
Q_{TE}(t) &= Pr[BE_1(t) \cup BE_2(t) \cup \dots \cup BE_n(t)] \\
&= 1 - Pr[BE_1^\circ(t) \cup BE_2^\circ(t) \cup \dots \cup BE_n^\circ(t)] \\
&= 1 - (Pr[BE_1^\circ(t)]Pr[BE_2^\circ(t)] \dots Pr[BE_n^\circ(t)]) \\
&= 1 - (q_1^\circ(t)q_2^\circ(t) \dots q_n^\circ(t)) \\
&= 1 - \prod_{i=1}^n q_i^\circ(t) \\
&= 1 - \prod_{i=1}^n [1 - q_i(t)]
\end{aligned} \tag{4.4}$$

where Q_{TE} denotes the probability of the TE at time t . q_i denotes the probability of the i^{th} BE for $i = 1, 2, \dots, n$. $\circ$ denotes that the event has not occurred.

Another fault properties are the minimal cut sets (MCSs), analysis of which provides qualitative insight into the potential failures mechanisms, such as possible combinations of BEs, that can result in the TE, and is particularly useful when FT is large or complex [164]. Specifically, a cut set is defined as a set of BEs that when occurred simultaneously leads to the TE [58]. When the set of distinct BEs in a cut set cannot be reduced further it is called MCS [58]. Thus, any MCS can be represented with an and-gate connected to all of its BEs and any TE represented with an or-gate connected to all MCSs, whose Boolean representation and probability are presented in Equation 4.5 and Equation 4.6, respectively. It is worth noting that the number of distinct BEs defines the order of the MCS and that a distinct BE can be a member of different MCSs [58].

$$TE(t) = MCS_1(t) \cup MCS_2(t) \cup \dots \cup MCS_n(t) \tag{4.5}$$

$$Q_{TE}(t) = 1 - \prod_{j=1}^k [1 - \check{Q}_j(t)] \tag{4.6}$$

where $\check{Q}_j(t)$ the probability of j^{th} MCS that can be derived using Equation 4.2.

Finally, another important quantitative fault property derived from FTA is the importance metrics, that measures the relative importance of a BE compared to other BEs with respect to the TE probability [58]. The importance depends on the probability of the BE and the location of the BE in the FT diagram [58], the most common of which are the following. The Birnbaum (BM) importance metric (I^{BM}) [178] indicates the sensitivity of the TE probability to the BE_i , as expressed in Equation 4.7. The Fussell-Vesely (FV) importance metric (I^{FV}) [179] indicates the probability that at least one MCS that contains the BE_i is failed at time t , given that the system is failed at time t [180], as expressed in Equation 4.8. The Criticality (CR) importance metric (I^{CR}) indicates the probability that BE_i caused TE at time t , knowing that the TE occurred at time t , as expressed in Equation 4.9.

$$I^{\text{BM}}(i|t) = \frac{\partial \mathcal{Q}_{\text{TE}}(t)}{\partial q_i(t)} \quad (4.7)$$

$$I^{\text{FV}}(i|t) \approx \frac{1 - \prod_{j=1}^{m_i} [1 - \check{\mathcal{Q}}_j^i(t)]}{\mathcal{Q}_{\text{TE}}(t)} \quad (4.8)$$

$$I^{\text{CR}}(i|t) = \frac{I^{\text{BM}}(i|t)q_i(t)}{\mathcal{Q}_{\text{TE}}(t)} \quad (4.9)$$

To conduct FTA, various commercial tools can be employed, such as ALD [181], BlockSim [182], AFRY [183], RiskSpectrum [184], and PTC Windchill [185]. FTA of this research is conducted in PTC Windchill, considering its simple interface, straightforward FT diagram construction, and automated calculation of fault properties, including TE probability of failure, importance measures, MCS, and more [170].

4.2 Digital Twins

4.2.1 Manoeuvring Model

4.2.1.1 Manoeuvring Modelling Group Model

For digital twin applications, numerical simulations of ship manoeuvring can be employed using either system-based methods that use mathematical models to express the manoeuvring motion as an ordinary differential equation according to

the Newton's second law [142] or computational fluid dynamics (CFD) methods that resolve the complex fluid-structure interactions by incorporating both viscous and rotational effects in the flow problem [186]. However, despite CFD simulations being considered complementary to the experimental methods due to their high-fidelity and growing computational power [187], their time-consuming aspect renders them impractical [188], especially when real-time or a significant number of simulations need to be conducted [189].

On the other hand, system-based methods are typically limited to three or four degrees of freedom (3DOF, 4DOF) [190] with their main advantage being the rapid computational time, despite their compromise on the accuracy for long-term manoeuvring simulations [189]. For instance, a system-based ship manoeuvring simulation of 150 s can be executed in 50 s on a typical Intel Core i7 @3.2 GHz processor [189], whereas a CFD-based simulation of 19 s can take 225 h on an Intel Xeon E5-2680 v2 @2.8 GHz processor [191]. The two most widely used system-based models are the Abkowitz model [192], also known as the whole ship model, which expresses the hydrodynamic forces and moments acting on a ship as Taylor series, and the manoeuvring modelling group (MMG) model [193], also known as the modular model, which decomposes the forces and moments acting on different components, typically the ship hull, propeller, and rudder [194]. Compared to the Abkowitz model that considers the ship as a whole, the MMG model is based on first principles that carry explicit and clear physical meaning of each component including their interactions [195]. In addition, it has the capability to accommodate different actuators configurations, such as single-screw [196], twin-screw [197], and twin azimuth thrusters [198], integrate external disturbances, such as currents, waves, and wind, and be combined with other numerical, experimental, or empirical methods [195].

To describe the manoeuvring motions, two coordinate systems are typically used, which are the space-fixed coordinate system $o_0-x_0y_0z_0$ and the body-fixed coordinate system $o_B-x_By_Bz_B$ [199], as presented in Figure 4.1. The origin o_B is assigned at the midship instead at the centre of gravity G , when a fixed position is needed regardless of the load condition. The x_0y_0 -plane and x_By_B -plane coincide with the still-water surface plane, whereas the x_B -axis is directed towards the bow and the z_0 -axis and z_B -axis are directed downwards. u and v denote the surge and sway velocities in the x_B -direction and y_B -direction, respectively. $\dot{\psi}$ denotes the yaw rate around z_B -axis,

where ψ denotes the heading angle from x_0 -axis to x_B -axis. $\dot{\phi}$ denotes the roll rate, where ϕ denotes the roll angle. U denotes the resultant velocity as $U = \sqrt{u^2 + v^2}$, and β denotes the drift angle as $\beta = \tan^{-1}(-v/u)$.

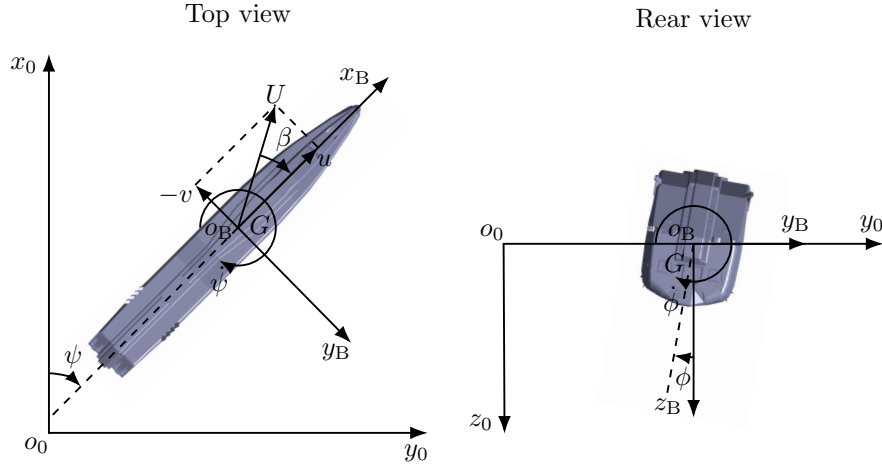


Figure 4.1 Top and rear views of the space-fixed coordinate system and body-fixed coordinate systems o_0 - $x_0y_0z_0$ and o_B - $x_By_Bz_B$, respectively.

The motion equations of a 4DOF MMG that couples the surge, sway, yaw, and roll motions, assuming that the heave and pitch motions are negligible, is expressed as [200]:

$$\left\{ \begin{array}{l} (m + m_{x_B})\dot{u} - (m + m_{y_B})v\dot{\psi} = X \\ (m + m_{y_B})\dot{v} + (m + m_{x_B})u\dot{\psi} + m_{y_B}\alpha_{y_B}\ddot{\psi} - m_{y_B}l_{y_B}\ddot{\phi} = Y \\ (I_{z_B} + J_{z_B})\ddot{\psi} + m_{y_B}\alpha_{y_B}\dot{v} = N - x_{B,G}Y \\ (I_{x_B} + J_{x_B})\ddot{\phi} - m_{y_B}l_{y_B}\dot{v} - m_{x_B}l_{x_B}u\dot{\psi} = K - W\overline{GM}\phi \end{array} \right. \quad (4.10)$$

where m , m_{x_B} , and m_{y_B} denote the ship's mass and the added mass in the x_B -direction and y_B -direction, respectively. I_{x_B} , I_{z_B} , J_{x_B} , and J_{z_B} denote the moment of inertia about the x_B -axis and z_B -axis, and the added moment of inertia in their corresponding axes, respectively. a_{y_B} denotes the x_B -coordinate of centre of m_{y_B} , while l_{x_B} and l_{y_B} denote the z_B -coordinates of the centres of m_{x_B} and m_{y_B} , respectively. $x_{B,G}$ denotes the x_B -coordinate of the centre of gravity, W denotes the weight of water displaced by the ship hull, and $\overline{GM}$ denotes the metacentric height. X , Y , N , and K denote the forces in the x_B -axis and y_B -axis, yaw moment about the midship, and roll moment about the centre of gravity, respectively.

4.2.2 Actuators Models

4.2.2.1 Rudder Dynamics Model

For digital twin applications, the rudder dynamics can be employed using a first-order linear differential equation, similar to many practical models [201, 202]. In order to mirror the dynamics of the rudder, two limiters, known as slew rates, are used to saturate the magnitude of its angle and deflection rate [202, 203], as presented in Figure 4.2. The rudder dynamics model is expressed as [204, 205]:

$$\dot{\delta} = \frac{\delta_C - \delta}{T_\delta} \quad (4.11)$$

where, $\dot{\delta}$ denotes the actual rudder deflection rate, whose maximum value should surpass the limit of 2.32 deg per s [206]. δ_C denotes the commanded rudder angle, whose maximum value should not exceed 35 deg [206]. T_δ denotes the time constant with typical values between 1–3 s [207].

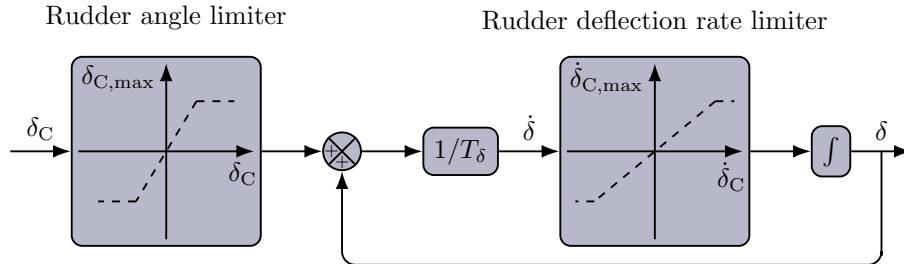


Figure 4.2 Block diagram of the rudder dynamics model.

4.2.2.2 Propeller Dynamics Model

For digital twin applications, the propeller dynamics can be employed using a first-order linear differential equation. In order to mirror the dynamics of the propeller, two slew rates are used to saturate the magnitude of its speed and speed rate to avoid overload of mechanical parts, such as the crankshaft [205], as presented in Figure 4.3. The propeller dynamics model is expressed as [208, 209]:

$$\dot{n} = \frac{n_C - n}{T_n} \quad (4.12)$$

where, $\dot{n}$ denotes the actual propeller revolution rate, whose maximum values should not exceed the limits specified by the engine manufacturer [210]. n_C denotes the commanded propeller revolution, whose maximum value should not exceed the limit set by the engine manufacturer [211]. n denotes the actual propeller revolution. T_n denotes the time constant [208].

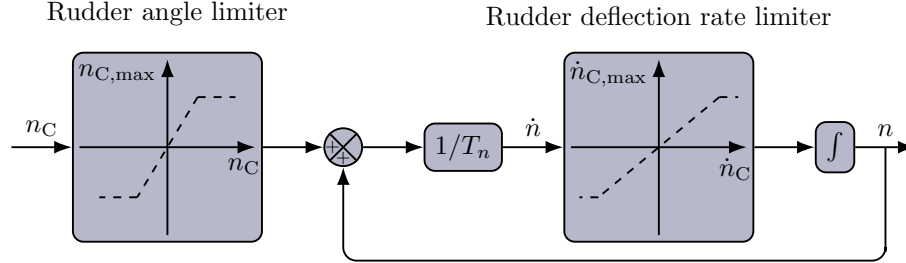


Figure 4.3 Block diagram of the propeller dynamics model.

4.2.3 Perception Sensor Model

4.2.3.1 Light Detection and Ranging Model

For digital twin applications, the perception sensor can be employed by modelling its fundamental measurement principle and its noise model. During reactive collision avoidance, where the temporal and spatial margins for error are limited, perception sensors that provide distance measurements from collision-inducing obstacles become essential [212], such as stereo-cameras, RADARs, and LIDARs. Stereo cameras passively capture electromagnetic waves using two pairs of monocular cameras and provide the cheapest option when it comes to extracting distance measurements [213]. However, they require complex and heavy image processing techniques to extract such information [214] and exhibit the lowest accuracy depending on the illumination conditions [215].

RADARs and LIDARs actively emit electromagnetic waves in the microwave and infrared spectrum, respectively, and use the time-of-flight principle of the pulses reflected from the obstacles to directly measure the distances [216]. RADARs are suitable for long-distance measurements of up to 10 NM and operation in all maritime environments [217]. However, the scanning frequency is low, approximately every 2–3 s, the measurements are limited only to 2 dimensions (2D), and the resolution and accuracy are low even at close distances, ranging from several to hundreds of m,

due to the relatively wide beams [218, 219].

In contrast, LIDARs exhibit the highest accuracy of distance and angular measurements due to their very narrow laser beams [220]. Scanning is conducted multiple times per s with each spin consisting of a few million measurements, allowing accurate distance, speed, position, and size estimation of the obstacles, as well as generation of a 3D map of the surrounding environment [218]. Typical LIDARs measure distances of up to a few hundred m with some reaching up to a few km [217, 221].

LIDARs are particularly susceptible to noise coming from the maritime environment, including seawater, rain, fog, and snow [218]. Water droplets in the atmosphere cause severe attenuation of the laser beams, absorb their energy, reduce the surface reflectivity of the obstacles, or cause pseudo-points from beams backscattered from the droplets that can be falsely detected as obstacles [222]. In addition, random noise can be produced by the sensor itself due to its intrinsic design limitations, discharges in the circuits, or during the conversion from analogue to digital signal [223]. Due to the many contributing factors that are hard to be known apriori [223], a common approach is to assume that the noise follows a Gaussian distribution [224], as presented in Figure 4.4. Hence, the time-of-flight equation of a LIDAR sensor with an added Gaussian noise model is expressed as [225]:

$$d_i = \frac{ct_i}{2} + \epsilon \quad (4.13)$$

where d_i denotes the distance of the i^{th} LIDAR measurement, c denotes the speed of light, t_i denotes the time of flight, and ϵ denotes the added noise that follows a Gaussian distribution with 0 mean and variance σ^2 . The total LIDAR measurements at each timestep t constitutes to the array $d_t = [d_{1,t}, d_{2,t}, \dots]$, where $i = 1$ starts refers to the most starboard LIDAR measurement.

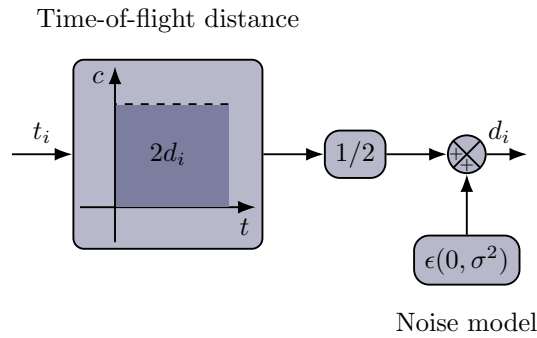


Figure 4.4 Block diagram of LIDAR time-of-flight measurement principle and its added noise model.

4.2.4 Map Model

4.2.4.1 Binary Occupancy Map Model

For digital twin applications, the map can be employed by modelling the spatial representation of the environment [146], such as the navigational area of the OS. Typical map representation methods are divided into topological maps, feature maps, and occupancy grid maps [226]. Topological maps use graphs, such as nodes and arcs, to represent the environment in the most compact way, but exhibit challenges in storing proximity information or modelling complex environments due to their simplicity [227]. Feature maps use parametric features, such as points and lines, to represent distinctive parts of the environment that are identifiable by the perception sensor, but they are not suitable for highly unstructured environments with no distinct geometries and when detailed navigation is needed due to its limited resolution [226].

Occupancy grid maps use grid of fixed resolution to represent the environment, where each cell stores a probability of being free or obstacle-occupied [228]. Their main advantages are their rich representation of the environment in both 2D and 3D, flexibility in balancing resolution with accuracy depending on the application requirements, and compatibility with noisy perception sensors, such as a LIDAR [229]. Thus, occupancy grid maps are commonly used to represent the navigational areas for path planning and collision avoidance applications [230], as presented in Figure 4.5.

To develop, customise, and integrate digital twins into a single virtual environment, various commercial tools can be employed, such as OpenAI Gym [231], Gazebo [232], SimPy [233], and MATLAB/Simulink [234]. The digital twins of this research are conducted in MATLAB/Simulink, due to the customisation capabilities of a wide range of digital twin libraries, including the Navigation Toolbox [235], LIDAR Toolbox [236], and Robotics System Toolbox [237].



Figure 4.5 (a) Satellite image of a navigational area captured using Google Maps.
(b) 2D occupancy grid map of the navigational area.

4.3 Deep Reinforcement Learning

The fundamental agent–environment $\mathcal{E}$ interaction within the MDP framework at each timestep t is boiled down into the agent receiving a state of the environment S_t and selecting an action A_t based on the received state that leads to the reception of a reward R_{t+1} and new state S_{t+1} [149], as presented in Figure 4.6. The sum of all rewards that the agent accumulates from timestep t and onwards through this interaction is known as the return $\mathcal{G}_t$, which is expressed as:

$$\mathcal{G}_t = R_t + R_{t+1} + R_{t+2} + \dots \quad (4.14)$$

However, considering the uncertainties of the future, the return is formulated as the expected discounted return, which is expressed as:

$$\mathcal{G}_t = R_t + \gamma R_{t+1} + \gamma^2 R_{t+2} + \dots = \sum_{i=t}^{\mathcal{T}} \gamma^{i-t} R_i \quad (4.15)$$

where $\gamma = [0, 1]$ denotes the discount rate, i denotes the timestep $i = [0, \mathcal{T}]$, and $\mathcal{T}$ denotes the terminal timestep.

The overall goal of the agent is to learn a policy π that maximises the expected return from its initial timestep $\mathcal{G}_0$ by mapping from states to actions. However, considering that the policy can be stochastic, the return $\mathcal{G}_0$ is formulated as an

expected return J , which is expressed as:

$$J = \mathbb{E}_{r_i, s_i \sim \mathcal{E}, a_i \sim \pi} [\mathcal{G}_0] \quad (4.16)$$

where, s_i , a_i , and r_i denote the values of the state, action, and reward, respectively.

To learn such a policy, the expected return at each timestep t and onwards after taking the action a_t in state s_t following the policy π needs to be learned, known as the action-value function $Q^\pi(s_t, a_t)$, which is expressed as:

$$Q^\pi(s_t, a_t) = \mathbb{E}_{r_{i \geq t}, s_{i > t} \sim \mathcal{E}, a_{i > t} \sim \pi} [\mathcal{G}_t \mid s_t, a_t] \quad (4.17)$$

The action-value function can be formulated in its recursive form using the Bellman equation, which is expressed as:

$$Q^\pi(s_t, a_t) = \mathbb{E}_{r_t, s_{t+1} \sim \mathcal{E}} [r(s_t, a_t) + \gamma \mathbb{E}_{a_{t+1} \sim \pi} [Q^\pi(s_{t+1}, a_{t+1})]] \quad (4.18)$$

Finally, the action-value function can be further simplified when a deterministic policy μ is used, which is expressed as:

$$Q^\mu(s_t, a_t) = \mathbb{E}_{r_t, s_{t+1} \sim \mathcal{E}} [r(s_t, a_t) + \gamma Q^\mu(s_{t+1}, \mu(s_{t+1}))] \quad (4.19)$$

Thus, the goal of the agent is to learn an optimal policy by accurately estimating the optimal action-value function at each timestep, thereby maximising the expected return.

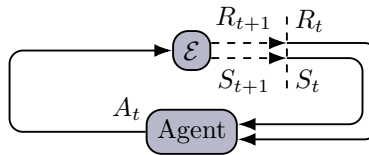


Figure 4.6 The agent–environment interaction in MDP.

4.3.0.1 Deep Deterministic Policy Gradient Algorithm

Different DRL-based agents can be employed to represent the decision-making agent that solves the MDP problem, where some of the most commonly used algorithms are the trust region policy optimisation [238], DDPG [239], proximal policy optimisation [240], soft actor-critic [241], and twin delayed DDPG (TD3) [242].

While each algorithm has its own advantages and disadvantages, choosing the most suitable one for each application is not a trivial effort. However, a comparative study evaluating the aforementioned algorithms for process control applications provides a good indication of the superior control performances of DDPG and TD3 algorithms [243]. In addition, DDPG algorithm is suitable for continuous and high-dimensional state and action spaces and challenging physical control problems with inertia and fine control of actions [244].

The DDPG algorithm is based on an actor-critic architecture, where the actor and the critic represent the policy $\mu(s \mid \theta^\mu)$ and action-value function $Q(s, a \mid \theta^Q)$, respectively, using deep neural networks (DNNs) as function approximators parameterised by their respective weights θ^μ and θ^Q . The actor and critic are referred to as the main actor network and main critic network, respectively, that constitute the main network. The actor and critic learn off-policy by utilising a replay buffer $\mathcal{D}$ of finite size that stores the tuples (s_t, a_t, r_t, s_{t+1}) generated from the environment at each timestep t . Particularly, the actor and critic are updated by uniformly sampling a minibatch $\mathcal{B}$ of tuples (s_i, a_i, r_i, s_{i+1}) from the replay buffer to minimise the correlations between the samples, where $i = [1, b]$ and b denotes the size of the minibatch.

Based on the prior Equation (4.18), the targets for the learning of the critic is expressed as:

$$y_i = r_i + \gamma Q(s_{i+1}, \mu(s_{i+1} \mid \theta^\mu) \mid \theta^Q) \quad (4.20)$$

However, since the action-value function is updated while in the target, it leads to divergence in learning. To tackle this, DDPG algorithm employs a target network, which is a copy of the main network. Specifically, the target actor network $\mu'(s \mid \theta^{\mu'})$ and target critic network $Q'(s, a \mid \theta^{Q'})$ with their respective weights $\theta^{Q'}$ and $\theta^{\mu'}$ are used to give stable targets, which is expressed as:

$$y_i = r_i + \gamma Q'(s_{i+1}, \mu'(s_{i+1} \mid \theta^{\mu'}) \mid \theta^{Q'}) \quad (4.21)$$

Thus, the main critic network learns by minimising the critic loss, which is expressed as:

$$L(\theta^Q) = \frac{1}{N} \sum_{i=1}^N (y_i - Q(s_i, a_i \mid \theta^Q))^2 \quad (4.22)$$

and by updating its weights in the direction of gradient descent that minimises the

loss, which is expressed as:

$$\theta^Q \leftarrow \theta^Q - a_Q \nabla_{\theta^Q} L \quad (4.23)$$

where a_Q denotes the learning rate of the main critic network.

The main actor network learns by minimising the actor loss, which is expressed as:

$$J(\theta^\mu) = -\frac{1}{N} \sum_{i=1}^N Q(s_i, \mu(s_i | \theta^\mu) | \theta^Q) \quad (4.24)$$

and by updating its weights in the direction of gradient ascent that maximises the expected return, which is expressed as:

$$\theta^\mu \leftarrow \theta^\mu + a_\mu \nabla_{\theta^\mu} J \quad (4.25)$$

where a_μ denotes the learning rate of the main actor network.

The target actor network and target critic network learn by updating their weights using soft target updates, which are expressed as:

$$\theta^{Q'} \leftarrow \tau \theta^Q + (1 - \tau) \theta^{Q'} \quad (4.26)$$

$$\theta^{\mu'} \leftarrow \tau \theta^\mu + (1 - \tau) \theta^{\mu'} \quad (4.27)$$

where $\tau \ll 1$ denotes the target smooth factor.

It is worth noting that every tuple of the replay buffer are normalised for effective learning, known as batch normalisation. Also, noise sampled from a noise process $\mathcal{W}$, such as an Ornstein-Uhlenbeck process, is added to the main actor network's output to encourage exploration. A pseudo-code and schematic diagram of the algorithm are presented in Algorithm 1 and Figure 4.7.

To customise, employ, and train DRL-based agents, various commercial tools can be employed, such as TensorFlow [245], PyTorch [246], OpenAI [231], Keras [247], and MATLAB/Simulink [234]. The DRL-based agent of this research is conducted in MATLAB/Simulink, due to the customisation capabilities of a wide range of machine learning libraries, including the Reinforcement Learning Toolbox [248].

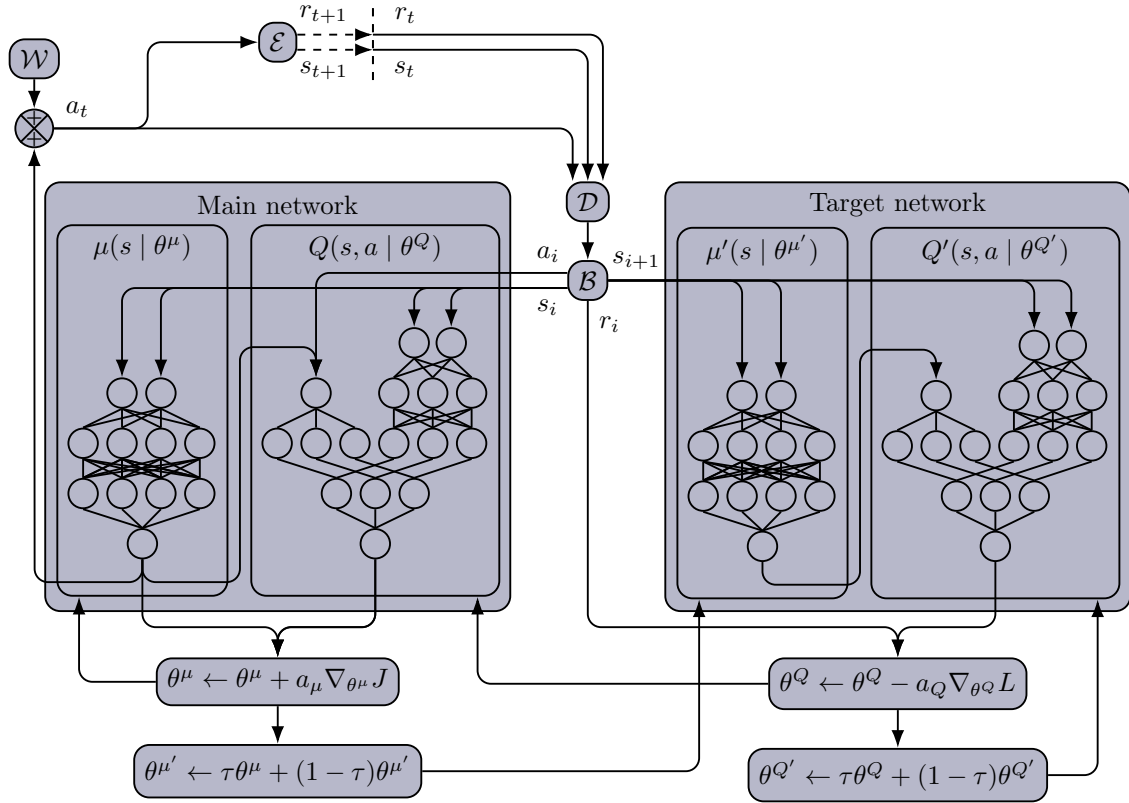


Figure 4.7 Block diagram of the DDPG algorithm.

4.4 Deep Learning

4.5 Feedforward Neural Networks

Different DL-based agents can be employed for the classification problem, where some of the most commonly used algorithms are the feedforward neural network (FNN) [249], recurrent neural network [250], convolutional neural networks [251], long short-term memory networks [252], multilayer perceptrons [253], generative adversarial networks [254], and transformer networks [255]. The FNN is the simplest DL-based agent, which has achieved high accuracy on many classification problems [256].

Specifically, a FNN consists of input and output layers, with one or more hidden layers in between them, where information flows only in one direction, from the input to the output layer [257]. The new representation from a previous layer is obtained via various activation functions, such as rectified linear unit [156]. The FNN is

trained using the training data, where the weights of each neuron are updated by adjusting their values in the direction that minimises the classification error, known as back propagation [258].

To customise, employ, and train DRL-based agents, various commercial tools can be employed, such as TensorFlow [245], PyTorch [246], Keras [247], Caffe [259], ONNX [260], and MATLAB/Simulink [234]. The DRL-based agent of this research is conducted in MATLAB/Simulink, due to the customisation capabilities of a wide range of machine learning libraries, including the Reinforcement Learning Toolbox [248].

Chapter 5

Reference System & Case Studies Setup

5.1 Reference System

The reference ship is a single-screw high-speed container ship, known as the S-175 [200]. The S-175 is selected, as it is one of the benchmark hull forms used in manoeuvring studies, due to its well-defined hydrodynamic coefficients [261]. For a container ship of this size, the 7S60ME-C10 marine two-stroke engine is selected, as it satisfies the power requirements of specified maximum continuous rating (SMCR) between 11,200–15,000 kW for container ships with deadweight tonnage between 26,500–33,000 tn [211]. The main particulars of the OS are presented in Table 5.1.

Table 5.1 Main particulars of the OS.

Particulars	Value
Length	175 m
Beam	25.4 m
Draft	8.5 m
Depth	11.0 m
Displaced volume	21,222 m ³
Block coefficient	0.559
Maximum commanded rudder angle ¹ , $\delta_{C,\max}$	35 deg
Maximum rudder deflection rate ² , $\dot{\delta}_{\max}$	5 deg/s
Time constant ³ , T_{δ}	1 s
Nominal propeller revolution at 85% SMCR, n_{nom}	99.5 rpm
Nominal speed, U_{nom}	10.41 m/s

¹ It should not exceed 35 deg according to the SOLAS, Regulation 29 [206]. A relatively small maximum commanded rudder angle is selected to reduce the roll effect [200]. ² It should exceed 2.32 deg/s according to the SOLAS, Regulation 29 [206]. ³ Typical values range between 1–3 s [207].

5.2 Case Studies

A total of five case studies are investigated, where the objective of each and related phases of the proposed research methodology is presented in Table 7.1.

Table 5.2 Case studies with their correlated low-level research objectives and phases.

Case study	Low-level research objectives	Phase
1	1	1
2	2, 5, 7, 8	2, 3, 5
3	5, 6, 7, 8	2, 3, 5
4	3, 5, 7, 8	2, 3, 5
5	4, 5, 7, 8	2, 3, 4, 5

5.2.1 Case Study 1

5.2.1.1 CAS design scope definition

The case study considers a short-sea shipping (SSS) operation. Limiting the operating scenario to SSS, which is defined as coastal trading with routes up to 800 NM [262, 263], is deemed to be a pivotal step to analyse the risk associated with the CAS before the full-scale implementation for transoceanic operations. The investigated ship is considered to operate autonomously only during the en route phase for a total of 730 h [79], which is equivalent to one month of operation prior to maintenance. Yet, the en route phase for cargo ships constitutes the most unsafe phase that contributes up to 40% of the total accident occurrences [264].

Four different operating modes are investigated based on the combinations of weather and illumination conditions, as presented in Table 5.3. Specifically, good weather considers calm sea and good visibility, whereas adverse weather considers heavy sea state with restricted visibility. Currents are considered to exist in all weather conditions. Daylight and darkness illuminations consider 12 h from sunrise to sunset and 12 h from sunset to sunrise, respectively.

Table 5.3 Four operating modes based on different weather and illumination conditions.

	Daylight illumination	Darkness illumination
Good weather	Mode 1	Mode 2
Adverse weather	Mode 3	Mode 4

The high-level design requirements are as follows.

- The CAS complies to the degree of autonomy four according to IMO [12] to perform collision avoidance at the same cognitive level as a human operator without any intervention [52, 265].
- The CAS complies to the IMO instruments pertinent to collision avoidance to achieve safe collision avoidance amidst the MASSs and conventional ships coexistent maritime scene [266].

5.2.2 Case Study 2–5

A 4DOF MMG model is used, as released in the Marine Systems Simulator Toolbox [209], that considers the none-negligible roll-coupling effect in high-speed container ships with low metacentric height [267], such as the S-175. In addition, the model considers no environmental disturbances and it is assumed to provide sufficient fidelity, as 3DOF is often sufficient in most manoeuvring studies [268].

5.2.2.1 OS Safety Domain Model Customisation & Internal Risk Metrics Integration

The probability of CAS failure is considered as the critical internal risk metric. Specifically, a circular safety domain (SD) model is customised to dynamically increase its size based on the probability of failure (POF), which is a function of operating time t expressed as:

$$SD(t) = SD_{t_0}(1 + POF(t)/k_0) \quad (5.1)$$

where $k_0 > 0$ denotes a coefficient.

5.2.2.2 Critical Collision Scenario Investigation & Critical Collision Risk Indices Identification

A 2D binary occupancy map is considered, assuming that in most surface-based applications the most critical information to be perceived is on the horizontal plane [269]. The size of the map is 5×5 km with resolution of 1×1 m, where each cell stores a binary value, 0 or 1, to represent a free or obstacle-occupied area, respectively. A single static or dynamic obstacle is encountered by the OS during its path following generated by two waypoints. Specifically, in both cases, the encounter leads to a collision on the path, should none of the vessels take any evasive action. It is worth noting that collision with static obstacles remains a challenging issue as global databases of maritime accidents suggest that 21% of 513 investigated collision accidents originated from strikes with other ships that were not underway using their engines, such as being engaged in fishing, moored, or at anchor [53]. The static

obstacle is modelled as a circle of 100 m radius to arbitrarily approximate the shape and size of any mid-sized ship, similar to the OS size.

A 2D LIDAR is considered, which is set to scan at the midship with a maximum detecting range of 1341 m. The area that exceeds this range constitutes the sensor's blind-spot zone, where no information can be derived from [270]. It is worth noting that the selected maximum detecting range is not arbitrary but it is comparative to the manoeuvrability of the OS. Specifically, assuming that the turning circle at the maximum rudder angle is a good indicator of the OS manoeuvrability [271], the ratio of the maximum detecting range to its maximum advance is 1.4. In addition, a forward scanning with 225 deg field of view is assumed to be sufficient among static obstacles, where an angular resolution of 5.63 deg constitutes a total of 41 LIDAR measurements that guarantees the detection of any circular obstacle with a radius greater than 65.8 m at its maximum detecting range. It should be mentioned that despite the state-of-the-art LIDARs reaching only up to 1 km in detection range [221], it is assumed that future advancements in sensor technology will realise the LIDAR specification requirements considered in these case studies.

The critical CRIs in such scenarios are identified as the relative distance and angles of the OS from the obstacle as physical values that quantify the safety from collision-inducing obstacles. The safety domain whose violation is considered is also identified as a critical CRI. The noise level of the perception sensor that determines the level of uncertainty of the relative distance is also identified as a critical CRI. Finally, the obstacle classification (*OC*) of the detected obstacles as static or dynamic and the compliance to CORLEGs during the evasive manoeuvres with dynamic obstacles are considered as critical CRIs.

5.2.2.3 Markov Decision Process Problem Formulation

5.2.2.3.1 Decision-Making Objectives-Based Reward Functions Modelling

The rewards that the agent learns to maximise are defined as reward functions, which are identified according to path following, nominal navigation, actuator control, and collision avoidance objectives. The path following reward is expressed as:

$$R_{1,t} = \begin{cases} k_1 + \frac{k_2}{e_{\text{XT},t}^2 + k_3} + \frac{k_4}{e_{\text{H},t}^2 + k_5 + k_6|e_{\text{XT},t}|}, & \text{if } |e_{\text{XT},t}| \leq \text{XTL} \\ \frac{k_2}{e_{\text{XT},t}^2 + k_3} + \frac{k_4}{e_{\text{H},t}^2 + k_5 + k_6|e_{\text{XT},t}|}, & \text{if } |e_{\text{XT},t}| > \text{XTL} \end{cases} \quad (5.2)$$

where $k_1, k_2, k_3, k_4, k_5, k_6 > 0$ denote the coefficients, e_{H} denotes the heading error of the OS from the path as $e_{\text{H}} = \psi_{\text{WP}} - \psi$ given the heading of the path $\psi_{\text{WP}} = \arctan(y_2 - y_1, x_2 - x_1)$ from two waypoints (x_1, y_1) and (x_2, y_2) , e_{XT} denotes the cross-track error of the OS from the path as $e_{\text{XT}} = -(x - x_1)\sin(\psi_{\text{WP}}) + (y - y_1)\cos(\psi_{\text{WP}})$ [272], and XTL denotes the threshold for the path following criterion often refer to as the cross-track limit [273]. It can be inferred that the reward is maximised when the cross-track and heading errors of the OS from the path are minimised concurrently. Also, an additional constant reward k_1 is given when the OS follows the path within the given threshold.

The nominal navigation reward is expressed as:

$$R_{2,t} = k_7 v_t^2 + k_8 \dot{\psi}_t^2 + k_9 \dot{v}_t^2 + k_{10} \ddot{\psi}_t^2 \quad (5.3)$$

where $k_7, k_8, k_9, k_{10} < 0$ denote the coefficients. It can be inferred that the reward is maximised when the sway and yaw velocities and accelerations of the OS are minimised.

The rudder and propeller control rewards are expressed as:

$$R_{3,t} = k_{11} \delta_{\text{C},t}^2 + k_{12} \dot{\delta}_{\text{C},t}^2 \quad (5.4)$$

$$R_{4,t} = k_{13} (n_{\text{C},t} - n_{\text{norm}})^2 + k_{14} \dot{n}_{\text{C},t}^2 \quad (5.5)$$

where $k_{11}, k_{12}, k_{13}, k_{14} < 0$ denote the coefficients. It can be inferred that the reward is maximised when the magnitude and the rate of the actuators are minimised.

The collision avoidance reward is expressed as:

$$R_{5,t} = k_{15} d_t + k_{16}, \text{ if } d_t > SD \quad (5.6)$$

where $k_{15} > 0$ and $k_{16} < 0$ denote the coefficients, and SD denotes the threshold for the collision criterion. It can be inferred that the reward is maximised when the distances of the OS from the obstacles are maximised.

The COLREG-compliance reward is expressed as:

$$R_{6,t} = k_{15}e^{k_{16}d_t} + k_{17}, \text{ if } d_{i,t} > SD \text{ and } i \leq i_{6 \text{ deg}} \quad (5.7)$$

where $k_{15}, k_{16} < 0, k_{17} > 0$ denote the coefficients, SD denotes the threshold for the collision criterion, and $i_{6 \text{ deg}}$ denotes the LIDAR measurement from which the relative angle between the OS and the obstacle is smaller than 6 deg. Specifically, the $i_{6 \text{ deg}}$ is the threshold for all LIDAR measurements from the most starboard one until the most forward one up to 6 deg. It can be inferred that the reward is minimised when the OS conducts evasive manoeuvre with the obstacle being on its starboard side, which is against the COLREG.

The final reward function is expressed as:

$$R_t = R_{1,t} + R_{2,t} + R_{3,t} + R_{4,t} + R_{5,t} \quad (5.8)$$

5.2.2.3.2 Critical Collision Risk Indices Integration Into State Space

The state space with integrated critical CRIs is expressed as:

$$S_t = [\psi_t, u_t, \dot{u}_t, v_t, \dot{v}_t, r_t, \dot{r}_t, U_t, \dot{U}_t, e_{\text{XT},t}, \dot{e}_{\text{XT},t}, \ddot{e}_{\text{XT},t}, e_{\text{H},t}, \dot{e}_{\text{H},t}, \ddot{e}_{\text{H},t}, d_t, \mathcal{N}, SD, \dot{SD}, \ddot{SD}, OC] \quad (5.9)$$

It is worth noting that despite noise being added on the perception sensor measurements observation d , an additional noise variance observation $\mathcal{N}$ is added to represent the value of the noise variance σ^2 of the perception sensor, as presented prior in Equation (4.13). The magnitude of the safety domain size, its rate, and acceleration are all incorporated into the state space for a higher resolution of this critical CRI. Finally, the obstacle classification is incorporated as a binary measure, where 0 indicates the absence of obstacle, -1 the presence of a static obstacle, and 1 the presence of a dynamic obstacle.

5.2.2.3.3 Propeller-Rudder Coupled Control Integration Into Action Space

The propeller-rudder coupled action space is expressed as:

$$A_t = [\delta_{\text{C},t}, n_{\text{C},t}] \quad (5.10)$$

5.2.2.4 DRL-Based Agent Training Framework Development

5.2.2.4.1 Hyperparameters setting

A DDPG agent is employed, whose main hyperparameters pertaining to the network's architecture are two hidden layers with 600 neurons each for the actor network and two hidden layers with 500 neurons each for the critic network constituting to a total of 396,001 and 281,001 learnable parameters including their weights, respectively.

5.2.2.4.2 Scenarios & Collision Risk Indices Training Envelope Definition

A representation of investigated case study is presented in Figure 5.1. In each episode, the OS is always initiated at the first waypoint and at nominal navigation conditions at n_{nom} heading towards the next waypoint. In addition, the noise variance of the LIDAR is randomly generated between $\sigma^2 = [0, 25]$ m², the safety domain is randomly generated between $SD = [12.7, 203.2]$ m, and the static or dynamic obstacle is randomly generated with equal probability $OC = [-1, 1]$. Finally, the simulation timestep and update iteration step of the agent are set to 1 s to be compatible with real-time applications.

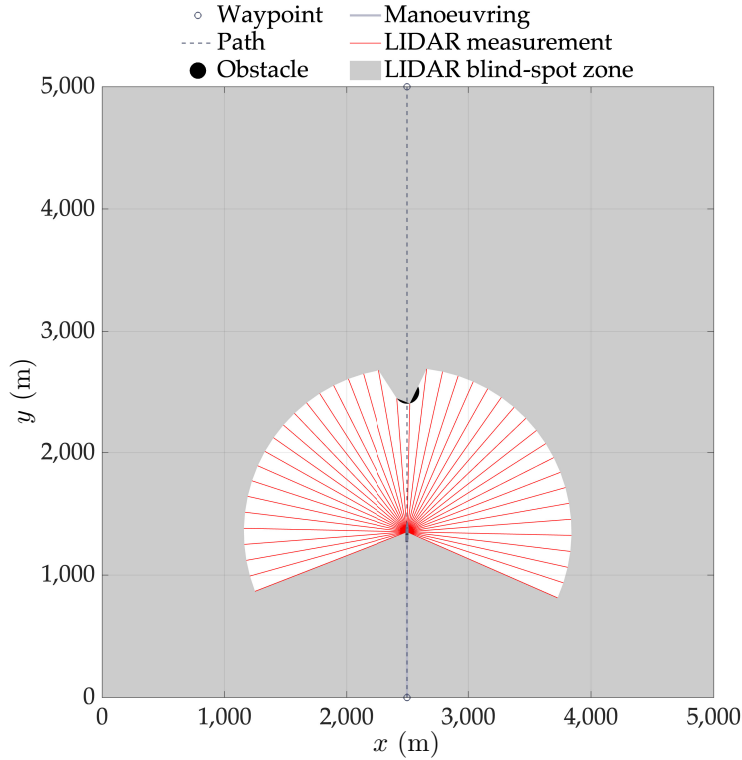


Figure 5.1 Representation of the investigated case study.

5.2.2.4.3 Obstacle Classification Data Generation

The acquired obstacle classification data are pertaining to locally generated measurements, including the velocities and accelerations of the OS, which are the $u, v, r, \dot{u}, \dot{v}, \dot{r}$, and the LIDAR measurements, specifically the index number of the LIDAR measurement i , and the magnitude, its velocity, and acceleration values, which are the $d_{i,t}, \dot{d}_{i,t}, \ddot{d}_{i,t}$. Along with the generated data, the respective labels are acquired considering the absence of an obstacle, presence of a static obstacle, and presence of a dynamic obstacle.

5.2.2.5 Robustness Metrics Definition

Four robustness metrics are defined pertaining to path following (RM_{PF}), collision avoidance (RM_{CA}), collision avoidance efficiency (RM_{CAE}), and COLREG-compliance (RM_{CC}), which are expressed as:

$$RM_{PF,\times} = |e_{\text{XT},\times}| < TH_{PF} = B/2 \quad (5.11)$$

$$RM_{CA,*} = \min(d_*) > TH_{CA} = SD \quad (5.12)$$

$$RM_{CAE,*} = -\text{sign}(XT_{obs} * XT_{OS}) \min(d_*) \geq TH_{CAE} = 0 \quad (5.13)$$

$$RM_{CC,*} = \text{sign}(i_* - i_{6 \text{ deg}}) \min(d_*) > 0 = SD \quad (5.14)$$

where $\times$ and $*$ denote the timesteps of the first and minimum obstacle detection, respectively, and TH their respective thresholds. It can be inferred that the robustness for path following requires cross-track error within a margin prior to the first obstacle detection, whereas the robustness for collision avoidance requires sufficient distance from the obstacles at the minimum obstacle detection. Robustness for collision avoidance efficiency requires evasive action opposite to the direction of the obstacle compared to the path at the minimum obstacle detection, which leads to a more efficient collision avoidance in terms of minimum travel distance and consequently minimisation of fuel consumption. Robustness for COLREG compliance requires evasive action from the OS with the detected obstacle at its port-side at the minimum obstacle detection. Further details of case studies 2–5 are presented in Table 5.4.

Table 5.4 Case studies with their correlated low-level research objectives and phases.

Case study	Obstacle	Propeller revolution	Safety domain	Perception Sensor	Critical CRI	Robustness metrics
2	Static	Constant (n_{norm})	Dynamic	Ideal	Relative distance, relative angle, internal risk-informed dynamic safety domain	RM_{PF}, RM_{CA}
3	Static	Dynamic	Static	Ideal	Relative distance, relative angle	RM_{CA}
4	Static	Constant (n_{norm})	Static	Noisy	Relative distance, relative angle, perception sensor noise level	RM_{PF}, RM_{CA}
5	Static, dynamic	Constant (n_{norm})	Static	Ideal	Relative distance, relative angle, COLREG, obstacle classification	RM_{CAE}, RM_{CC}

Chapter 6

Results & Discussion

6.1 Case Study 1

6.1.0.1 International Maritime Organisation Instruments Review

In order to comply with the degree of autonomy four according to the IMO [12], the CAS needs to follow the typical human decision-making process. This process can be translated into its equivalent system functions [266] that are highly intertwined and interdependent.

- Information acquisition
- Information analysis
- Decision making
- Action execution

Additionally, in order to comply with the IMO instruments pertinent to collision avoidance, the COLREG [274] and the SOLAS/Chapter V [206] are reviewed. Specifically, the key concepts related to collision avoidance are identified to extrapolate the functional and system requirements for the CAS, as presented in Figures 6.1–6.1. For instance, the rule for the ship to proceed at all times at a safe speed (COLREG/Rule 6) is extrapolated as a functional requirement for the CAS to discern the safe speed and as a system requirement to control it in every quarter situation. Thus, the main systems of the CAS and their functional requirements are as follows.

- Situation Awareness System (SAS) – acquires all the necessary state data of

the Own Ship (OS), TSs, and surrounding environment to appraise the quarter situation (COLREG/Rule 5).

- Decision-Making System (DMS) – assesses the collision risk and makes the appropriate collision avoidance decision corresponding to action commands to mitigate the collision risk, determine the safe speed and distance, and exit from the quarter situations (COLREG/Rule 8).
- Intention Communication System (ICS) – communicates the mutual evasive intentions, emergency, or distress between the OS and TSs of the quarter situation to make the collision avoidance intentions apparent and in timely manner (COLREG/Rule 28).
- Action Execution System (AES) – activates and controls the necessary actuators to successfully execute the collision avoidance decisions (COLREG/Rule 17).

The main systems can be decomposed into their hierarchically lower subsystems. The subsystems and their functional requirements in terms of their expected input and output are listed in Table 6.1.

Table 6.1 Subsystems of the CAS and their functional requirements in terms of their expected input and output.

System level 1	System level 2	System level 3	Input	Output	Relevant regulation
CAS	SAS	Medium-range scanning system	Light, image, etc.	Obstacle tracking, distance data, etc.	COLREG/Rule 7.c
		Long-range scanning system	Radio frequency data, etc.	Distance data, speed data, direction data, etc.	COLREG/Rule 7.b
		Environment perception system	Temperature data, humidity data, etc.	Weather analysis, weather warnings, etc.	COLREG/rule 28
		Sound perception system	Acoustic signals, contextual data, etc.	Sound recognition, sound localisation, etc.	SOLAS/Chapter V/Regulation 19.2.1.8
		Own-state perception system	Satellite signals, accelerometer data, gyroscope data, etc.	Position, orientation, velocity, time, etc.	SOLAS/Chapter V/Regulation 19.2.1.1
		Nautical chart system	Nautical information, survey data, meteorological data, etc.	Nautical charts, warnings, reports, etc.	SOLAS/Chapter V/Regulation 27
	DMS	Computing system	Location data, warnings, etc.	Action commands, future trajectory, good seamanship, etc.	SOLAS/Chapter V/Regulation 15.5
ICS	Light signalling system	Light signalling system	Control signal, etc.	light, visual information, etc.	COLREG/Rule 22
		Shape signalling system	Video signal, control signal, etc.	Visual information, etc.	COLREG/Rule 27
		Sound signalling system	Control signal, etc.	Acoustic signal, etc.	COLREG/Rule 33
		Wireless communication system	Text data, image data, audio data, etc.	Transmitted data, warnings, etc.	SOLAS/Chapter V/Regulation 14.4
AES	Power plant system	Power plant system	Fuel, water, control signal, etc.	Electrical power, thrusting power, heat, etc.	COLREG/Rule 19.b
		Shafting & steering system	Power, control signal, etc.	Propulsion power, speed control, etc.	SOLAS/Chapter V/Regulation 25

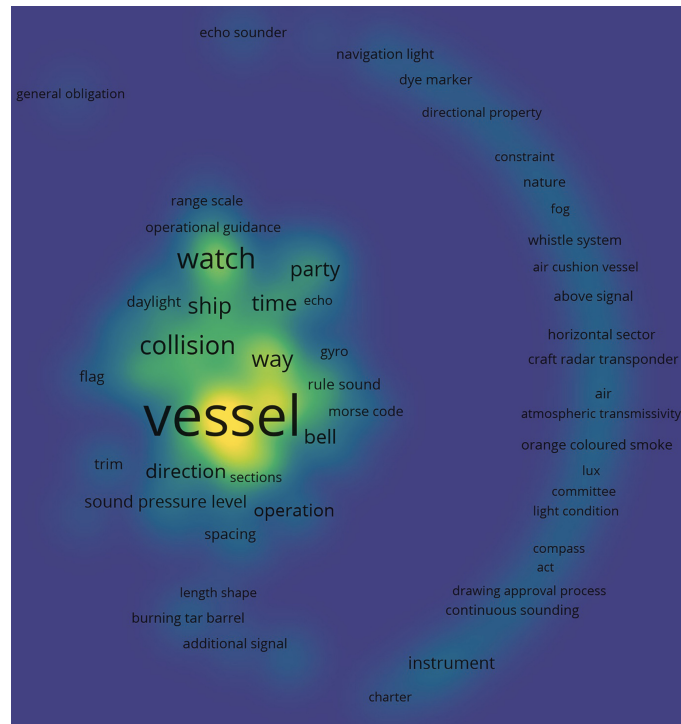


Figure 6.1 Density map of COLREG.

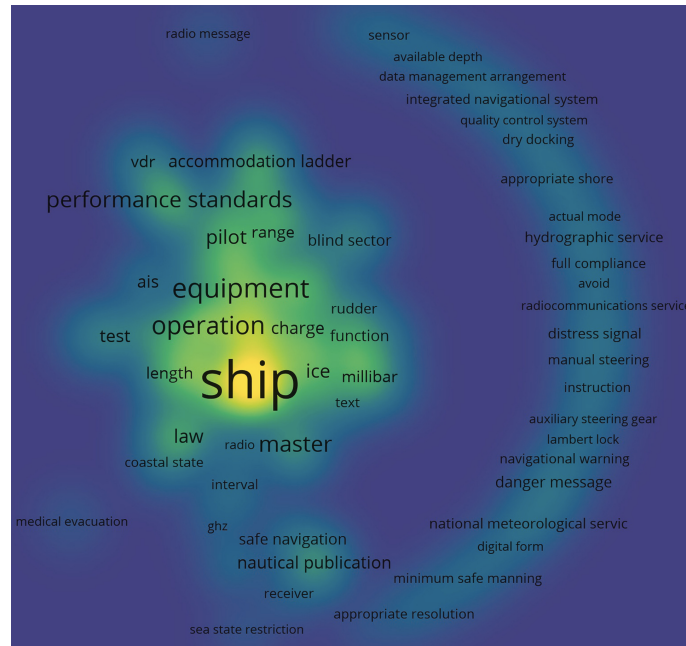


Figure 6.2 Density map of SOLAS/Chapter V.

6.1.0.2 Baseline Collision Avoidance System Configuration

The case study specific customisation needed for the baseline CAS configuration are the requirements for two masthead lights (COLREG/Rules 23.a.i-ii), two side lights for the starboard and port sides (COLREG/Rule 21.b), and five all-round lights (COLREG/Rules 28, 34.b.iii, 34.d, 36). The mode specific customisation is listed in

Table 6.2.

Table 6.2 Four operating modes based on different weather and illumination conditions.

Component	Mode 1	Mode 2	Mode 3	Mode 4	Relevant regulation
LCD panels	✓	×	✓	×	COLREG/Rule 20.d
Navigational lights	×	✓	✓	✓	COLREG/Rules 20.b–c
Towing light	×	×	×	×	COLREG/Rule 24
Flashing light	×	×	×	×	COLREG/Rule 23
Anemometer	×	×	✓	✓	COLREG/Rule 6
Visibility & weather sensor	×	×	✓	✓	COLREG/Rule 6

The derived system and functional requirements are used to develop a baseline CAS configuration at the component level, as presented in Table 6.3 and Figure 6.3. Particularly, the configuration consists of the following components groups.

- Components that are explicitly mentioned in the IMO instruments, such as the ECDIS (SOLAS/Chapter V/Regulation 19.2.1.4).
- Components that satisfy the requirements of “other means”, such as the inertial navigation system (INS) that can substitute the standard magnetic compass (SOLAS/Chapter V/Regulations 19.2.1.1, 19.2.2.6) by providing accurate attitude and position information in addition to the heading readings [275].
- Components that are not explicitly mentioned in the instruments but reflect the state-of-the-art technology, such as the LIDAR that can provide point clouds of the three-dimensional space [276], thus, further support the full appraisal of the quarter situation (COLREG/Rule 5).

However, it should be mentioned that despite the known limitations of some components for MASSs, such as the conventional Power Plant System [277], they are still included in the baseline CAS configuration considering the current limitation of alternative systems [52, 54]. Redundancy is introduced for a few components, such as the ECDIS to comply with the requirement of a backup arrangement (SOLAS/Chapter V/Regulations 19.2.1.5, 19.2.2.6). Redundancy is also introduced for the computer hardware and AI software for being the core decision-making components [278]. Finally, four day/night & thermal cameras and four LCD panels are arranged to ensure 360 deg of visual lookout and shape signal communication, respectively.

Table 6.3 Components list of the baseline CAS configuration and their functional competence.

System level 3	Component	Function	Relevant regulation
Medium-range scanning system	LIDAR	High-resolution three-dimensional scanning observation, tracking, and identification within the detectable range with depth measurements [276].	COLREG/Rule 5
	Day/night & thermal camera	High-resolution visual observation, tracking, and identification over sea at within the visible field of view even in total darkness and adverse weather, such as fog, rain, or snow [279].	COLREG/Rule 5
Long-range scanning system	AIS	Automatic ship-to-ship or ship-to-shore communication of the ship's navigational related information, such as the ship's identity, type, position, course, speed, and navigational status, monitoring, and tracking [206].	SOLAS/Chapter V/Regulation 19.2.4
	RADAR	Velocity and distance measurements for the identification, tracking, and positioning of other TSs, obstructions, shorelines, and navigational marks [206].	SOLAS/Chapter V/Regulation 19.2.3.2
Environment perception system	Visibility & weather sensor	Visibility and present weather condition measurement, such as fog density, precipitation, haze, smoke, and mist [280].	SOLAS/Chapter V/Regulation 5
	Anemometer	Magnitude of wind speed and direction measurement [281].	SOLAS/Chapter V/Regulation 5
	Current profiler	Magnitude of underwater currents and direction [282].	COLREG/Rule 6.a.v
	Echo sounder	Bathymetric measurement of the seabed [206].	SOLAS/Chapter V/Regulation 19.2.3.1
Sound perception system	Microphone	Sound signals and direction capturing [206].	SOLAS/Chapter V/Regulation 19.2.1.8
Own-state perception system	GNSS	True heading, position, velocity, and rate of turn measurement [206].	SOLAS/Chapter V/Regulation 19.2.1.6
	INS	Heading, attitude, and positional data measurement [275].	SOLAS/Chapter V/Regulation 19.2.1.1
Nautical chart system	ECDIS	Ship's route planning and monitoring based on nautical charts and nautical publications [206].	SOLAS/Chapter V/Regulation 19.2.1.4
Computing system	Computer hardware	Collision avoidance decision making [206].	SOLAS/Chapter V/Regulation 15.5
	AI software	Collision avoidance decision making [206].	SOLAS/Chapter V/Regulation 15.5

Light signalling system	Stern light	Ship's navigational status-related information, distress, or collision avoidance intention communication [274].	COLREG/Rule 22
	Masthead light	Ship's navigational status-related information, distress, or collision avoidance intention communication [274].	COLREG/Rule 22
	Side light	Ship's navigational status-related information, distress, or collision avoidance intention communication [274].	COLREG/Rule 22
	All-round light	Ship's navigational status-related information, distress, or collision avoidance intention communication [274].	COLREG/Rule 22
	Towing light	Ship's navigational status-related information, distress, or collision avoidance intention communication [274].	COLREG/Rule 22
	Flashing light	Ship's navigational status-related information, distress, or collision avoidance intention communication [274].	COLREG/Rule 22
Sound signalling system	Speaker	Ship's navigational status-related information, distress, or collision avoidance intention communication [274].	COLREG/Rule 33
Shape signalling system	LCD panel	Ship's navigational status-related information, distress or collision avoidance intention communication [274].	COLREG/Rule 27
Wireless communication system	Radio system	Ship's navigational status-related information, distress, collision avoidance intention, or weather communication [206].	SOLAS/Chapter V/Regulation 19.2.1.6
	LTE system	Ship's navigational status-related information, distress, or collision avoidance intention communication [274].	SOLAS/Chapter V/Regulation 19.2.1.6
Power plant system	Diesel generator	Electrical power generation [283].	COLREG/Rule 19.b
	Electrical system	Generated electrical power management and distribution to shipboard systems [206].	COLREG/Rule 19.b
	Cooling water system	Heat transfer from machinery using a cooling media, such as sea or fresh water [284].	COLREG/Rule 19.b
	Fuel system	Piping systems for fuel oil bunkering, storage, transfer, offloading, and treatment [206].	COLREG/Rule 19.b
	Main engine	Mechanical power generation for the ship propulsion [283].	COLREG/Rule 19.b
Shafting & steering system	Shafting	Mechanical power transfer from the engine to the propeller [285].	COLREG/Rule 19.b
	Steering gear	Torsional force generation to turn the rudder [206].	SOLAS/Chapter V/Regulation 25

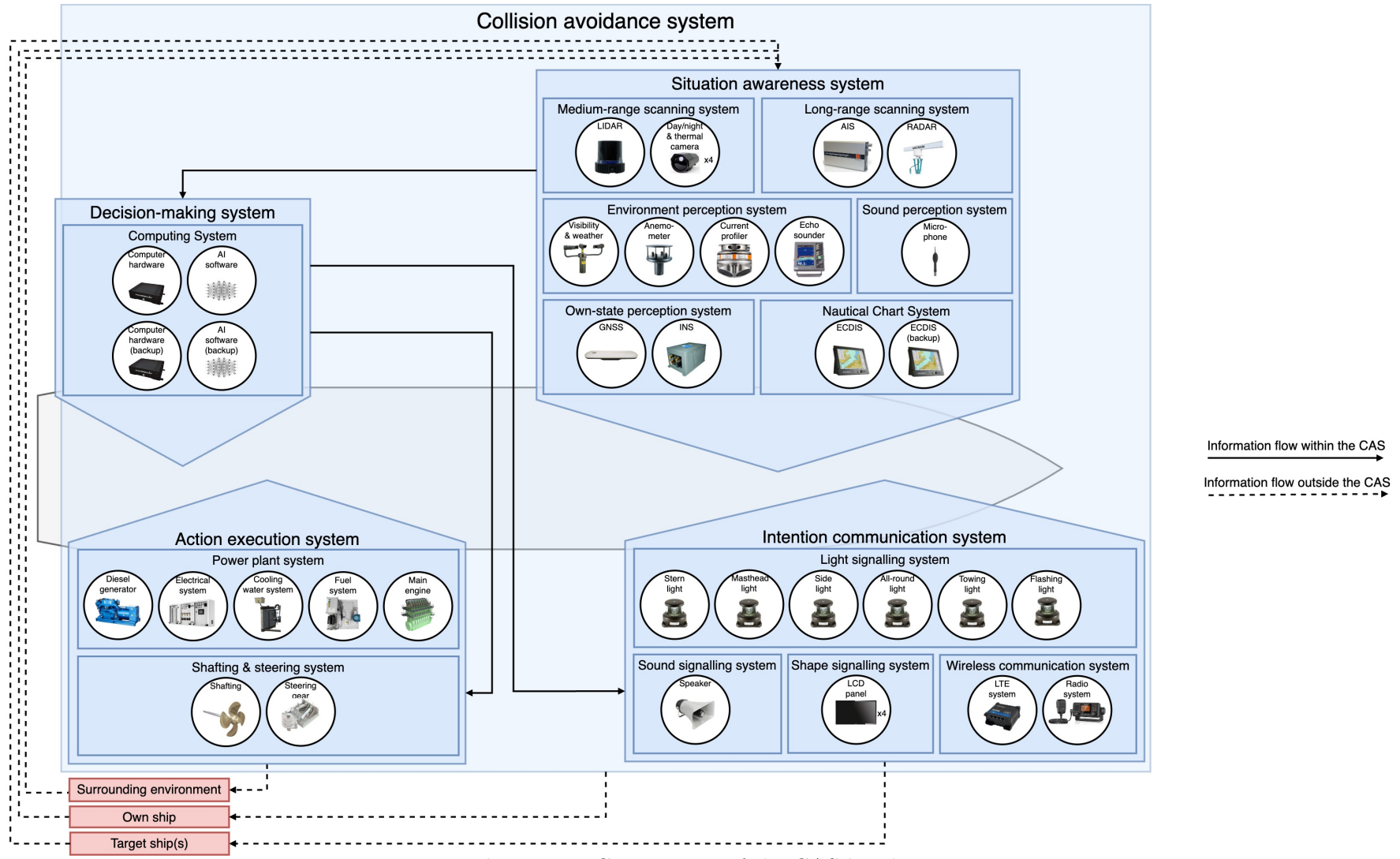


Figure 6.3 Components of the CAS baseline.

A graphical representation of the developed FT diagram and description of each event is presented in Figure 6.4 and Table 6.4, respectively. It should be mentioned that regarding the power plant system and shafting & steering system, risk-reducing measures have already been conducted in [284] within the MASS framework. For this reason, these systems are not further analysed into their components but considered as a single propulsion & steering component. Or-gates are used for components with no functional diversity [286], such as the visibility & weather sensor, anemometer, current profiler, and echo sounder. And-gates are used for components with functional diversity, such as the INS and GNSS. Vote-gates are used for redundant components, such as the ECDIS.

Table 6.4 Description of the events in the developed FT diagram.

Event	Description	Event	Description
TE	CAS failure	BE ₁₁	Echo sounder failure
IE ₁	SAS failure	BE ₁₂	GNSS failure
IE ₂	Medium-range scanning system failure	BE ₁₃	INS failure
IE ₃	Long-range scanning system failure	BE ₁₄	Microphone failure
IE ₄	Environment perception system failure	BE ₁₅	ECDIS failure
IE ₅	OS perception system failure	BE ₁₆	ECDIS ¹ failure
IE ₆	Nautical chart system failure	BE ₁₇	Computer hardware failure
IE ₇	DMS failure	BE ₁₈	Computer hardware ¹ failure
IE ₈	Computing system failure	BE ₁₉	AI software failure
IE ₉	Computing system ¹ failure	BE ₂₀	AI software ¹ failure
IE ₁₀	ICS failure	BE ₂₁	Stern light failure
IE ₁₁	Light signalling system failure	BE ₂₂	Masthead light failure
IE ₁₂	Shape signalling system failure	BE ₂₃	Side light failure
IE ₁₃	Wireless Communication System failure	BE ₂₄	All-round light failure
BE ₁	LIDAR failure	BE ₂₅	Towing light failure
BE ₂	Day/night & thermal camera No.1 failure	BE ₂₆	Flashing light failure
BE ₃	Day/night & thermal camera No.2 failure	BE ₂₇	Speaker failure
BE ₄	Day/night & thermal camera No.3 failure	BE ₂₈	LCD panel No.1 failure
BE ₅	Day/night & thermal camera No.4 failure	BE ₂₉	LCD panel No.2 failure
BE ₆	AIS failure	BE ₃₀	LCD panel No.3 failure
BE ₇	RADAR failure	BE ₃₁	LCD panel No.4 failure
BE ₈	Visibility & weather sensor failure	BE ₃₂	Radio system failure
BE ₉	Anemometer failure	BE ₃₃	LTE system failure
BE ₁₀	Current profiler failure	BE ₃₄	Propulsion & steering system

¹ Backup

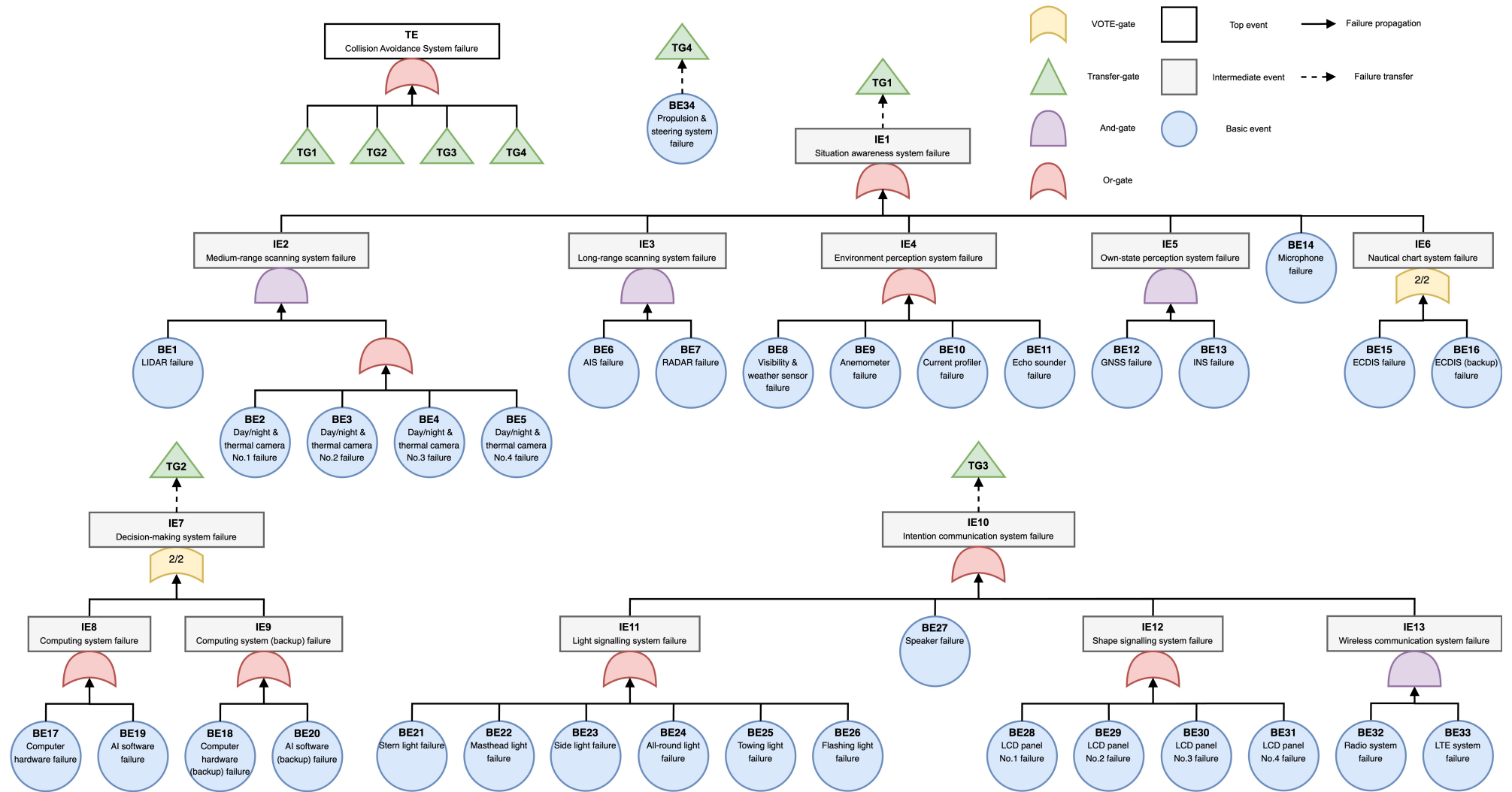


Figure 6.4 Developed FT diagram for the CAS baseline.

6.1.0.3 Failure Data Acquisition

To quantitatively analyse a FT diagram and derive pertinent risk metrics, the BEs need to be embedded with appropriate input data, such as the probability of failure, failure rate, or MTBF [53]. MTBF is a basic reliability measure of stochastic nature that is equal to the inverse of the failure rate and denotes the mean time between two successive failures [287] usually presented in units of hours. The use of MTBF data enables the modelling of continuous-time FTs that considers the evolution of a system failure over time [170]. It enables the investigation of the accident event rather than the total downtime after the accident [288], which is the primary focus of safety-critical autonomous systems. Finally, it enables the risk analysis of new systems when time, practicality, scarcity of data, and pace of technology development are their biggest barriers [289].

The MTBF data acquisition is based on the following assumptions.

- MTBF of each component is statistically independent [170].
- MTBF is independent of external influences of the operating conditions, such as variations of humidity, temperature, and stress levels [289].
- MTBF considers constant failure rate in the normal operating period of the “bathtub curve” [288].
- MTBF is restored after repair [290] but the components are non-repairable during the operation [291].

The acquired MTBF data based on the available literature and reported data are presented in Table 6.5. It is worth mentioning that considering all the uncertainties pertaining to the actual system, emphasis shall be given on the order of magnitude and not on the exact values of the acquired data [292]. Finally, the MTBF is acquired even for the non-repairable components, such as the navigational lights, which is a commonly accepted practice [185, 289].

Table 6.5 Acquired MTBF data for each BE.

BE	Component	MTBF ($\times 10^3$ h)
BE ₁	Quanergy Systems “M1 Edge”	60
BE ₂₋₅	DAT – CON “CLRT/HD-400”	20.2
BE ₆	Kongsberg Maritime “AIS 300S”	100
BE ₇	Micra “REKA”	87.6
BE ₈	MicroStep-MIS “VPF-730”	56.7
BE ₉	MicroStep-MIS “Windsonic 75 Anemometer”	131.4
BE ₁₀	Sonardyne “Syrinx”	225
BE ₁₁	Nautel Sonar “NESDF”	20
BE ₁₂	Kongsberg Maritime “SEANAV 300 Series”	45
BE ₁₃	Teledyne Marine “MK31”	16
BE ₁₄	BKSV “UA-1404”	40
BE ₁₅₋₁₆	Moxa “MPC-122-K Series”	39.675
BE ₁₇₋₁₈	MarineNav “LEVIATHAN 17i FANLESS”	100
BE ₁₉₋₂₀	-	40
BE ₂₁₋₂₆	Oxley “Series 1” & “Series 2”	30
BE ₂₇	Zenitel “VML-1520”	1,500
BE ₂₈₋₃₀	Litemax “DLF/DLH1968-U”	70
BE ₃₁	Danphone “DCB 9140 IP”	50
BE ₃₂	Teltonika Networks “RUT950”	270
BE ₃₃	MicroStep-MIS “VPF-730”	42.048

6.1.1 Quantitative Risk Analysis & Criticality Analysis

The probabilities of failure derived from the FTA are presented in Table 6.6 and Figure B.1-Figure B.11. The results indicate that the lowest probability of failure exhibits the CAS in mode 1 being as low as 11% when operated for 730 h. The CAS in mode 3 exhibits the highest probability of failure reaching up to 32%. The percentage contributions of each IE to the TE indicate that the ICS is the most critical main system, followed by the SAS. Specifically, the probability of failure of the ICS reaches from 4% in mode 1 as high as 25% in mode 3.

Table 6.6 Probability of failures of the TE and IEs.

Event	Description	Q			
		Mode 1	Mode 2	Mode 3	Mode 4
TE	CAS failure	1.14×10^{-1}	2.76×10^{-1}	3.18×10^{-1}	2.89×10^{-1}
IE	SAS failure	5.89×10^{-2}	5.89×10^{-2}	7.61×10^{-2}	7.61×10^{-2}
IE	DMS failure	6.36×10^{-4}	6.36×10^{-4}	6.36×10^{-4}	6.36×10^{-4}
IE	ICS failure	4.14×10^{-2}	2.16×10^{-1}	2.48×10^{-1}	2.16×10^{-1}
IE	AES failure	1.72×10^{-2}	1.72×10^{-2}	1.72×10^{-2}	1.72×10^{-2}

The derived Importance measures are provided in Table 6.8. The first notable observation is that the ranking concerning the order of magnitude is consistent across all Importance measures and modes, except for the speaker and LTE system. Considering that the two factors affecting the Importance measures are the location of the BEs in the FT diagram and their input data [64], this consistency suggests the embedment of reasonable MTBF data and the robustness of the developed FT diagram to represent the failure of the CAS. This is particularly pivotal for this early design phase considering the great uncertainties pertaining to the actual CAS design that is currently unknown. This also suggests that no sensitivity analysis is required at this design phase.

In addition, the robustness of the FT diagram enables the identification of the most critical components that exhibit the highest Importance measures. The results indicate that the BEs with the highest Importance measures are the echo sounder, navigational lights, microphone, visibility & weather sensor, propulsion & steering system, LCD panels, anemometer, current profiler, and speaker. It can be deduced that 67% of them are components of the ICS, followed by 28% of the SAS.

Table 6.7 Importance measures of the BEs in each mode.

BE	I^B			
	Mode 1	Mode 2	Mode 3	Mode 4
Echo sounder	1.00	1.00	1.00	1.00
Stern light		1.00	1.00	1.00
Masthead light No.1–2		1.00	1.00	1.00
Starboard-side light		1.00	1.00	1.00
Port-side light		1.00	1.00	1.00
All-round light No.1–5		1.00	1.00	1.00
Microphone	1.00	1.00	1.00	1.00
Propulsion & steering system	1.00	1.00	1.00	1.00
Visibility & weather sensor			1.00	1.00
LCD panel No.1–4	1.00		1.00	
Anemometer			1.00	1.00
Current profiler	1.00	1.00	1.00	1.00
LIDAR	1.42×10^{-1}	1.42×10^{-1}	1.42×10^{-1}	1.42×10^{-1}
GNSS	4.46×10^{-2}	4.46×10^{-2}	4.46×10^{-2}	4.46×10^{-2}
INS	1.61×10^{-2}	1.61×10^{-2}	1.61×10^{-2}	1.61×10^{-2}
Speaker	1.00	1.00	1.00	1.00
AI software ¹	2.54×10^{-2}	2.54×10^{-2}	2.54×10^{-2}	2.54×10^{-2}
Day/night & thermal camera No.1–4	1.21×10^{-2}	1.21×10^{-2}	1.21×10^{-2}	1.21×10^{-2}
ECDIS ¹	1.82×10^{-2}	1.82×10^{-2}	1.82×10^{-2}	1.82×10^{-2}
Computer hardware ¹	2.54×10^{-2}	2.54×10^{-2}	2.54×10^{-2}	2.54×10^{-2}
AIS	8.30×10^{-3}	8.30×10^{-3}	8.30×10^{-3}	8.30×10^{-3}
RADAR	7.27×10^{-3}	7.27×10^{-3}	7.27×10^{-3}	7.27×10^{-3}
LTE system	1.45×10^{-2}	1.45×10^{-2}	1.45×10^{-2}	1.45×10^{-2}
Radio system	2.70×10^{-3}	2.70×10^{-3}	2.70×10^{-3}	2.70×10^{-3}

¹ Or backup.

Table 6.8 Importance measures of the BEs in each mode.

BE	I^{FV}, I^{CR}			
	Mode 1	Mode 2	Mode 3	Mode 4
Echo sounder	2.99×10^{-1}	1.12×10^{-1}	9.47×10^{-2}	1.06×10^{-1}
Stern light		7.54×10^{-2}	6.35×10^{-2}	7.13×10^{-2}
Masthead light No.1–2		7.54×10^{-2}	6.35×10^{-2}	7.13×10^{-2}
Starboard-side light		7.54×10^{-2}	6.35×10^{-2}	7.13×10^{-2}
Port-side light		7.54×10^{-2}	6.35×10^{-2}	7.13×10^{-2}
All-round light No.1–5		7.54×10^{-2}	6.35×10^{-2}	7.13×10^{-2}
Microphone	1.51×10^{-1}	5.67×10^{-2}	4.78×10^{-2}	5.36×10^{-2}
Propulsion & steering system	1.44×10^{-1}	5.40×10^{-2}	4.55×10^{-2}	5.11×10^{-2}
Visibility & weather sensor			3.38×10^{-2}	3.79×10^{-2}
LCD panel No.1–4	8.65×10^{-2}		2.74×10^{-2}	
Anemometer			1.46×10^{-2}	1.64×10^{-2}
current profiler	2.70×10^{-2}	1.02×10^{-2}	8.56×10^{-3}	9.61×10^{-3}
LIDAR	1.43×10^{-2}	5.39×10^{-3}	4.53×10^{-3}	5.09×10^{-3}
GNSS	5.99×10^{-3}	2.25×10^{-3}	1.90×10^{-3}	2.13×10^{-3}
INS	5.99×10^{-3}	2.25×10^{-3}	1.90×10^{-3}	2.13×10^{-3}
Speaker	4.06×10^{-3}	1.53×10^{-3}	1.29×10^{-3}	1.44×10^{-3}
AI software ¹	3.83×10^{-3}	1.44×10^{-3}	1.21×10^{-3}	1.36×10^{-3}
Day/night & thermal camera No.1–4	3.58×10^{-3}	1.35×10^{-3}	1.13×10^{-3}	1.27×10^{-3}
ECDIS ¹	2.77×10^{-3}	1.04×10^{-3}	8.78×10^{-2}	9.86×10^{-4}
Computer hardware ¹	1.54×10^{-3}	5.79×10^{-4}	4.87×10^{-4}	5.47×10^{-4}
AIS	5.04×10^{-4}	1.89×10^{-4}	1.59×10^{-4}	1.79×10^{-4}
RADAR	5.04×10^{-4}	1.89×10^{-4}	1.59×10^{-4}	1.79×10^{-4}
LTE system	3.27×10^{-4}	1.23×10^{-4}	1.03×10^{-4}	1.16×10^{-4}
Radio system	3.27×10^{-4}	1.23×10^{-4}	1.03×10^{-4}	1.16×10^{-4}

¹ Or backup.

The MCS results are presented in Table 6.9. First, it can be noted that the MCSs are of order 1 or 2. MCSs with lower order are more critical [64] since a cut set with fewer BEs is more likely to be in a failure state [170]. In addition, a BE contained in many different MCSs is critical as it contributes more towards the failure of the whole system [293].

The components that exhibit the most vulnerable failure mechanisms are the echo sounder, followed by the navigational lights, microphone, propulsion & steering system, visibility & weather sensor, LCD panels, anemometer, current profiler, AI software and its backup, and computer hardware and its backup. It is worth mentioning that 48% of all MCSs are components of the ICS, followed by 36% of the

SAS.

Finally, the effectiveness of redundancy in reducing the pertinent risk metrics can be noted, whether in terms of identical components or functional diversity. For instance, despite INS and echo sounder exhibiting the lowest MTBF, adding functional diversity to the INS through the GNSS leads to a reduction of its criticality of up to two orders of magnitude both as a component and failure mechanism compared to the echo sounder.

Table 6.9 Probability of failures of the MCSs in each mode.

MCS	Q			
	Mode 1	Mode 2	Mode 3	Mode 4
{Echo sounder}	2.99×10^{-1}	1.12×10^{-1}	9.47×10^{-2}	1.06×10^{-1}
{Masthead light No.1}		7.54×10^{-2}	6.35×10^{-2}	7.13×10^{-2}
{Masthead light No.2}		7.54×10^{-2}	6.35×10^{-2}	7.13×10^{-2}
{Starboard-side light}		7.54×10^{-2}	6.35×10^{-2}	7.13×10^{-2}
{Port-side light}		7.54×10^{-2}	6.35×10^{-2}	7.13×10^{-2}
{All-round light No.1}		7.54×10^{-2}	6.35×10^{-2}	7.13×10^{-2}
{All-round light No.2}		7.54×10^{-2}	6.35×10^{-2}	7.13×10^{-2}
{All-round light No.3}		7.54×10^{-2}	6.35×10^{-2}	7.13×10^{-2}
{All-round light No.4}		7.54×10^{-2}	6.35×10^{-2}	7.13×10^{-2}
{All-round light No.5}		7.54×10^{-2}	6.35×10^{-2}	7.13×10^{-2}
{Stern light}		7.54×10^{-2}	6.35×10^{-2}	7.13×10^{-2}
{Microphone}	1.51×10^{-1}	5.67×10^{-2}	4.78×10^{-2}	5.36×10^{-2}
{Propulsion & steering system}	1.44×10^{-1}	5.40×10^{-2}	4.55×10^{-2}	5.11×10^{-2}
{Visibility & weather sensor}			3.38×10^{-2}	3.79×10^{-2}
{LCD panel No.1}	8.65×10^{-2}		2.74×10^{-2}	
{LCD panel No.2}	8.65×10^{-2}		2.74×10^{-2}	
{LCD panel No.3}	8.65×10^{-2}		2.74×10^{-2}	
{LCD panel No.4}	8.65×10^{-2}		2.74×10^{-2}	
{Anemometer}			1.46×10^{-2}	1.64×10^{-2}
{Current profiler}	2.70×10^{-2}	1.02×10^{-2}	8.56×10^{-3}	9.61×10^{-3}
{INS, GNSS}	5.99×10^{-3}	2.25×10^{-3}	1.90×10^{-3}	2.13×10^{-3}
{Speaker}	4.06×10^{-3}	1.53×10^{-3}	1.29×10^{-3}	1.44×10^{-3}
{Day/night & thermal camera No.1, LIDAR}	3.58×10^{-3}	1.35×10^{-3}	1.13×10^{-3}	1.27×10^{-3}
{Day/night & thermal camera No.2, LIDAR}	3.58×10^{-3}	1.35×10^{-3}	1.13×10^{-3}	1.27×10^{-3}
{Day/night & thermal camera No.3, LIDAR}	3.58×10^{-3}	1.35×10^{-3}	1.13×10^{-3}	1.27×10^{-3}
{Day/night & thermal camera No.4, LIDAR}	3.58×10^{-3}	1.35×10^{-3}	1.13×10^{-3}	1.27×10^{-3}
{ECDIS ¹ }	2.77×10^{-3}	1.04×10^{-3}	8.78×10^{-4}	9.86×10^{-4}
{AI software ¹ }	2.73×10^{-3}	1.03×10^{-3}	8.64×10^{-4}	9.70×10^{-4}
{AI software ² , computer hardware}	1.10×10^{-3}	4.13×10^{-4}	3.47×10^{-4}	3.90×10^{-4}
{AI software, computer hardware ² }	1.10×10^{-3}	4.13×10^{-4}	3.47×10^{-4}	3.90×10^{-4}
{RADAR, AIS}	5.04×10^{-4}	1.89×10^{-4}	1.59×10^{-4}	1.79×10^{-4}
{Computer hardware ¹ }	4.41×10^{-4}	1.66×10^{-4}	1.40×10^{-4}	1.57×10^{-4}
{Radio system, LTE system}	3.26×10^{-4}	1.23×10^{-4}	1.03×10^{-4}	1.16×10^{-4}

¹ With backup. ² Backup.

6.1.2 Collision Avoidance System Re-Configuration

For brevity, risk-informed reconfiguration is conducted only for the CAS in mode 3 that exhibits the highest probability of failure. A typical cost-effective risk-reducing measure is to focus on the critical components and failure mechanisms by either using alternative components with better reliability or introducing redundancy [294]. However, considering that alternative components for MASSs are yet to be developed, redundancy is added to the relatively inexpensive but critical components of the ICS and SAS. These are the echo sounder, current profiler, visibility & weather sensor, anemometer, microphone, LCD panels, navigational lights, and speaker.

The FTA results of the risk-informed CAS reconfiguration are presented in Table 6.10, Table 6.11, Table 6.12 and Figure B.12-Figure B.14. The derived results indicate 3% probability of failure of the risk-informed CAS reconfiguration when operated for 730 h, which equals to a reduction of 91% compared to the previous baseline CAS configuration. This is attributed to the reductions of the probability of failures of the ICS from 25% to 0.6% and SAS from 8% to 0.5%. Particularly, the Importance measures of the critical components and probability of failures of the MCSs are reduced up to three and four orders of magnitude, respectively. Additionally, it is noted that the ranking of the order of magnitude of the Importance measures continues to be consistent, except for the LTE system. Both the reduction of the probability of failure of the risk-informed CAS reconfiguration and the consistency in the ranking of the Importance measures verify the robustness of the developed FT diagram that magnifies the effectiveness of risk-reducing measures when proper decision-making concerning the most critical components and failure mechanisms are taken in the right direction.

The derived results are compared against the values reported in the pertinent literature. [79] reported 5.5% probability of contact accidents for a remotely controlled ship during the operation of 720 h, which was attributed to probability of failures of 1.7%, 3.7%, 0.2%, corresponding to the AES, SAS, and DMS, respectively. For conventional ships [295], concluded that 0.26 collision accidents are estimated per year, which is equivalent to 2.17% probability of collisions per month. In both cases, the results range in the same order of magnitude as found in this study. However, it should be underlined that the failure of the CAS does not necessarily lead to a

collision accident, thus, the comparison of the results is facilitated only for verification purposes.

It is worth noting that in this risk-informed CAS reconfiguration, the AES is the major contributor to the failure of the overall system. This is aligned with the notion that mechanical components of MASSs, especially the Power Plant System, will have much higher failure rates compared to other systems [54, 296]. However, this observation adds another layer of interest as the propulsion & steering component already represents a risk-informed configuration as mentioned earlier with a backup main engine. This indicates the limitation of redundancy as an effective risk-reducing measure for the Power Plant System and the need for intelligent monitoring and health assessment systems and/or alternative power plants with higher reliability [297].

Finally, it should be mentioned that the component that exhibits the most considerable uncertainty in terms of its MTBF data is the AI software, due to the scanty operational and accident data in similar systems [52]. However, what is certain is that the AI software does fail [298] but in a different way than humans do with potentially more severe consequences [299], such as false object recognition due to incomplete training data set.

Table 6.10 Probability of failures of the TE and IEs and percentage contributions of each IE to the TE of the risk-informed CAS reconfiguration compared to the baseline CAS configuration in mode 3.

Event	Description	Baseline CAS configuration, mode 3	CAS re-configuration, mode 3
		Q	Q
TE	CAS failure	3.18×10^{-1}	2.84×10^{-2}
IE	SAS failure	7.61×10^{-2}	4.55×10^{-3}
IE	DMS failure	6.36×10^{-4}	6.36×10^{-4}
IE	ICS failure	2.48×10^{-1}	6.23×10^{-3}
IE	AES failure	1.72×10^{-2}	1.72×10^{-2}

Table 6.11 Importance measures of the BEs of the risk-informed CAS reconfiguration in mode 3.

BE	I^B	I^{FV}, I^{CR}	BE	I^B	I^{FV}, I^{CR}
Propulsion & steering system	1.00	5.99×10^{-1}	Day/night & thermal camera No.3	1.21×10^{-2}	1.49×10^{-2}
LIDAR	1.42×10^{-1}	5.97×10^{-2}	Day/night & thermal Camera No.4	1.21×10^{-2}	1.49×10^{-2}
Echo sounder ¹	3.58×10^{-2}	4.47×10^{-2}	ECDIS ¹	1.82×10^{-2}	1.16×10^{-2}
GNSS	4.46×10^{-2}	2.50×10^{-2}	Microphone ¹	1.81×10^{-2}	1.14×10^{-2}
INS	1.61×10^{-2}	2.50×10^{-2}	Computer hardware ¹	2.54×10^{-2}	6.42×10^{-3}
Stern light ¹	2.40×10^{-2}	2.01×10^{-2}	Visibility & weather sensor ¹	1.28×10^{-2}	5.69×10^{-3}
Masthead light No.1 ¹	2.40×10^{-2}	2.01×10^{-2}	LCD panel No.1 ¹	1.04×10^{-2}	3.74×10^{-3}
Masthead light No.2 ¹	2.40×10^{-2}	2.01×10^{-2}	LCD panel No.2 ¹	1.04×10^{-2}	3.74×10^{-3}
Starboard-side light ¹	2.40×10^{-2}	2.01×10^{-2}	LCD panel No.3 ¹	1.04×10^{-2}	3.74×10^{-3}
Port-side light ¹	2.40×10^{-2}	2.01×10^{-2}	LCD panel No.4 ¹	1.04×10^{-2}	3.74×10^{-3}
All-round light No.1 ¹	2.40×10^{-2}	2.01×10^{-2}	AIS	8.30×10^{-3}	2.10×10^{-3}
All-round light No.2 ¹	2.40×10^{-2}	2.01×10^{-2}	RADAR	7.27×10^{-3}	2.10×10^{-3}
All-round light No.3 ¹	2.40×10^{-2}	2.01×10^{-2}	LTE system	1.45×10^{-2}	1.36×10^{-3}
All-round light No.4 ¹	2.40×10^{-2}	2.01×10^{-2}	Radio system	2.70×10^{-3}	1.36×10^{-3}
All-round light No.5 ¹	2.40×10^{-2}	2.01×10^{-2}	Anemometer ¹	5.54×10^{-3}	1.07×10^{-3}
AI software ¹	2.54×10^{-2}	2.09×10^{-2}	Current profiler ¹	3.24×10^{-3}	3.65×10^{-4}
Day/night & thermal camera No.1	1.21×10^{-2}	1.49×10^{-2}	Speaker ¹	4.87×10^{-4}	8.23×10^{-6}
Day/night & thermal camera No.2	1.12×10^{-2}	1.49×10^{-2}			

¹ Or backup.

Table 6.12 Probability of failures of the MCSs of the risk-informed CAS reconfiguration in mode 3.

MCS	Q	MCS	Q
{Propulsion & steering system}	1.72×10^{-2}	{ECDIS ¹ }	3.32×10^{-4}
{Echo sounder ¹ }	1.29×10^{-3}	{AI software ¹ }	3.27×10^{-4}
{INS, GNSS}	7.18×10^{-4}	{Microphone ¹ }	3.27×10^{-4}
{Stern light ¹ }	5.78×10^{-4}	{Visibility & weather sensor ¹ }	1.64×10^{-4}
{Masthead light No.1 ¹ }	5.78×10^{-4}	{AI software ² , computer hardware}	1.32×10^{-4}
{Masthead light No.2 ¹ }	5.78×10^{-4}	{AI software, computer hardware ² }	1.32×10^{-4}
{Starboard-side light ¹ }	5.78×10^{-4}	{LCD panel No.1 ¹ }	1.08×10^{-4}
{Port-side light ¹ }	5.78×10^{-4}	{LCD panel No.2 ¹ }	1.08×10^{-4}
{All-round light No.1 ¹ }	5.78×10^{-4}	{LCD panel No.3 ¹ }	1.08×10^{-4}
{All-round light No.2 ¹ }	5.78×10^{-4}	{LCD panel No.4 ¹ }	1.08×10^{-4}
{All-round light No.3 ¹ }	5.78×10^{-4}	{RADAR, AIS}	6.04×10^{-5}
{All-round light No.4 ¹ }	5.78×10^{-4}	{Computer hardware ¹ }	5.29×10^{-5}
{All-round light No.5 ¹ }	5.78×10^{-4}	{Radio system, LTE system}	3.91×10^{-5}
{Day/night & thermal camera No.1, LIDAR}	4.29×10^{-4}	{Anemometer ¹ }	3.07×10^{-5}
{Day/night & thermal camera No.2, LIDAR}	4.29×10^{-4}	{Current profiler ¹ }	1.05×10^{-5}
{Day/night & thermal camera No.3, LIDAR}	4.29×10^{-4}	{Speaker ¹ }	2.37×10^{-7}
{Day/night & thermal camera No.4, LIDAR}	4.29×10^{-4}		

¹ With backup. ² Backup.

6.2 Case Study 2

6.2.1 DRL-Based Agent Training

The training performance of the agent in terms of the return per episode, actor loss per step, and critic loss per step is presented in Figure 6.5. It is noted that the return converges to a local maximum approximately from episode 3600. The critic loss converges to a local minimum from step 11×10^5 , as indicated by its moving median, which denotes that the critic converges to a stable estimation of the expected return. The actor loss exhibits an upward trend potentially towards a local minimum from step 6.5×10^5 , as indicated by its moving median. Despite the actor loss diverging from its local minimum from step 6.5×10^5 , maximum critic loss is noted around step 6.5×10^5 and the upwards trend of actor loss is aligned with the minimisation of actor loss.

The training is terminated at episode 3870, which constitutes a total of 1,319,302

steps and approximately 30 hours of training. The minimum and maximum values of the training performance metrics derived during the training and their respective moving medians at the end of the training are presented in Table 6.13. The size of the safety domain SD_{t_0} generated randomly at the beginning of each episode during the training in terms of its distribution is presented in Figure 6.6. The mean value of its distribution $\overline{SD}_{t_0} = 107.36$ m denotes that the agent is trained effectively from diverse scenarios of uniformly distributed random values.

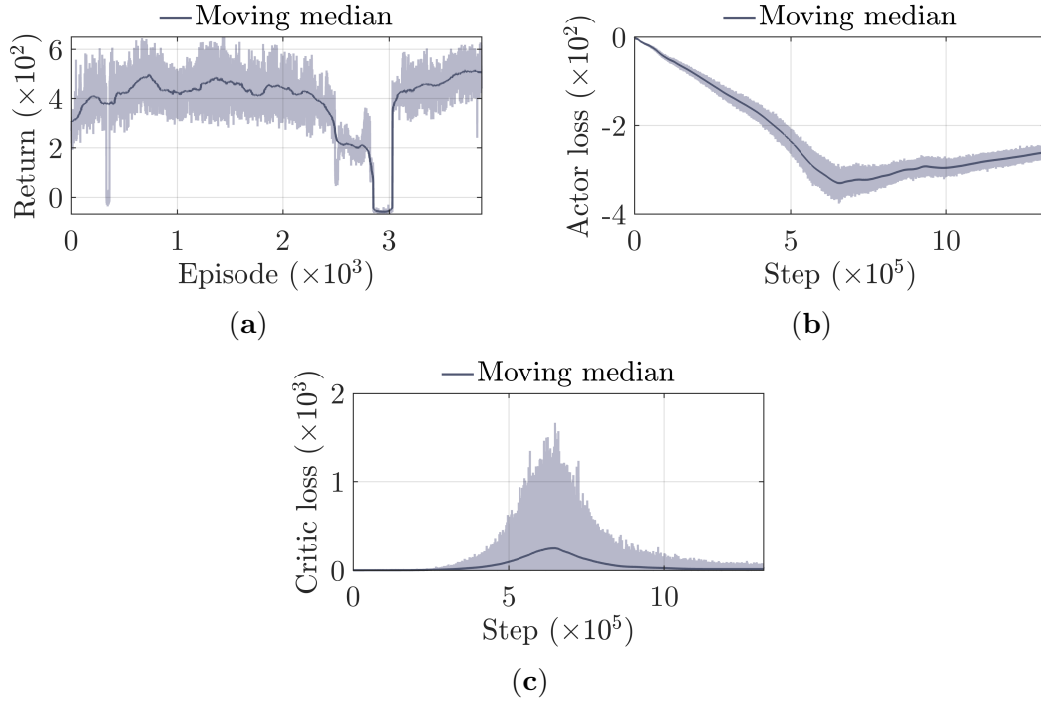


Figure 6.5 (a) Return per episode, (b) actor loss per step, and (c) critic loss per step during the training of agent. The sliding windows of their respective moving medians are 150 episodes and 25,000 steps.

Table 6.13 Training performance metrics during the training of agent.

Return _{min}	Return _{max}	Moving Median ¹
-68.12	649.83	506.62
Actor loss _{min}	Actor loss _{max}	Moving Median ²
-376.13	-0.39	-260.88
Critic loss _{min}	Critic loss _{max}	Moving median ²
1.60×10^{-3}	1,665.8	13.11

¹ At episode 3870. Sliding window of 150 episodes. ² At episode 3870. Sliding window of 25,000 steps.

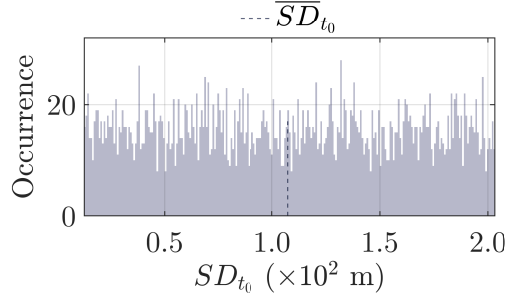


Figure 6.6 Distributions of random safety domain size SD_{t_0} generated at the beginning of each episode during the training of agent. The number of bins for each histogram is 250.

6.2.2 Decision-Making Agent's Robustness Verification

The trained agent is simulated in various scenarios within the trained envelope, but for brevity, only the results pertaining to $SD_{t_0} = [12.7, 101.60, 203.20]$ m, $x_{\text{obs}} = 2500$ m and $y_{\text{obs}} = 2500$ m are presented. The agent's decision-making in terms of the conducted manoeuvring in the static and dynamic scenarios is presented in Figure 6.7. The results are derived 3.57 times faster than the defined simulation timestep, which suggests the efficiency of employing the agent in real-time applications. Finally, considering that the timesteps $\times$ and $*$ refer to the first and minimum obstacle detections, respectively, each manoeuvring simulation is decomposed into three distinct stages as path following manoeuvre, evasive manoeuvre, and path recovery manoeuvre.

In the static scenarios it can be derived that the return that the agent accumulates is 632.33 when $SD_{t_0} = 12.7$ m, 521.85 when $SD_{t_0} = 101.60$ m, and 482.41 when $SD_{t_0} = 203.20$ m, which suggest that the agent conducts a bigger evasive manoeuvre when the size of the safety domain is bigger. Specifically, the ranges of the safety domain from the initial timestep t_0 to the terminal timestep t_T in each respective scenarios are $SD_{t_0-t_T} = [12.7, 16.61]$ m, $SD_{t_0-t_T} = [101.60, 133.15]$ m, and $SD_{t_0-t_T} = [203.20, 267.73]$ m. The actor's policy in terms of the commanded rudder angle δ_C per timestep t is presented in Figure 6.8. It is noted that the commanded rudder angles δ_C at the minimum obstacle detections are $\delta_C = -1.63$ deg when $SD_{t_0} = 12.7$ m, $\delta_C = 2.71$ deg when $SD_{t_0} = 101.60$ m, and $\delta_C = 5.03$ deg when $SD_{t_0} = 203.20$ m, as indicated by the timesteps $*$, which verifies the bigger evasive manoeuvre conducted when the safety domain size increases to transition to the path recovery phase.

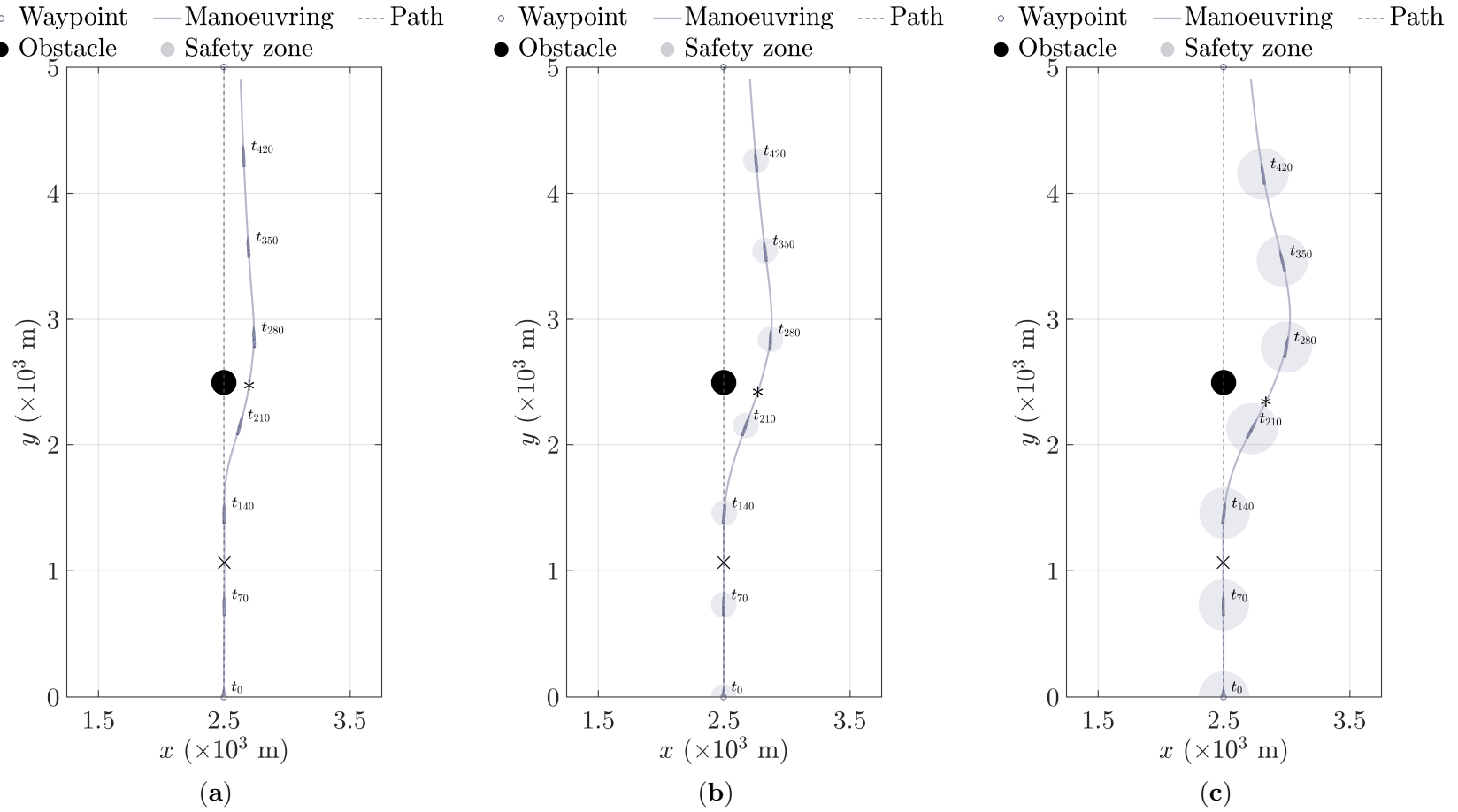


Figure 6.7 Decision-making of the agent in terms of the conducted manoeuvring when (a) $SD_{t_0} = 12.7$ m, (b) $SD_{t_0} = 101.60$ m, and (c) $SD_{t_0} = 203.20$ m. The position of the OS is plotted every 70 s. The $\times$ and $*$ represent the timesteps of the first and minimum obstacle detection, respectively.

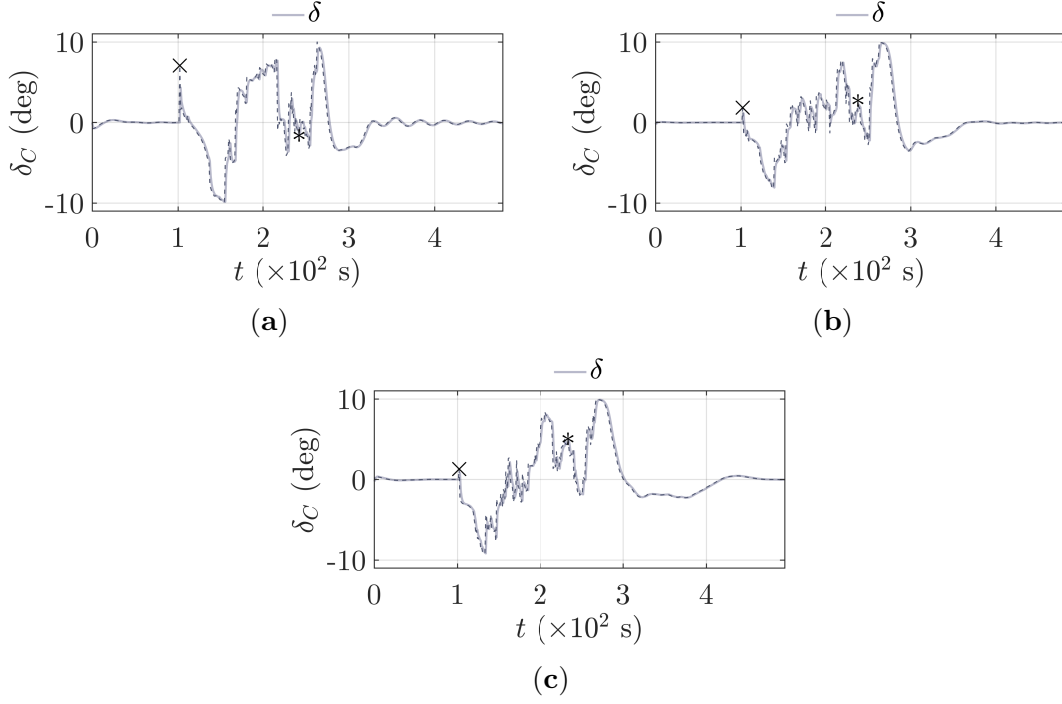
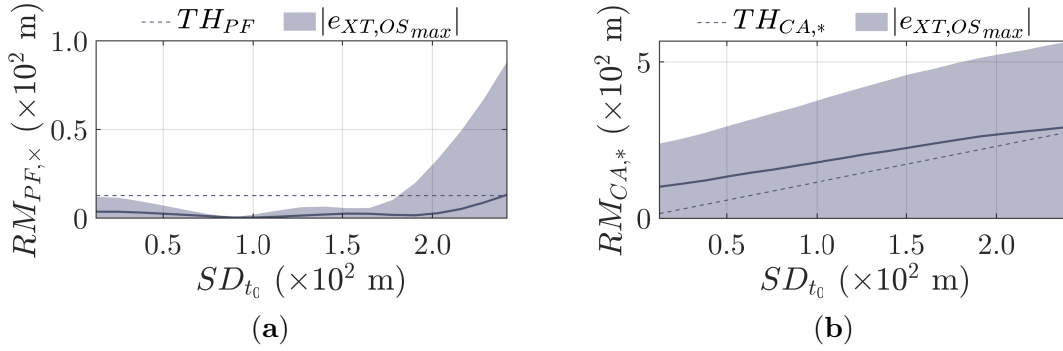


Figure 6.8 Actor’s policy of the agent in terms of the commanded rudder angle δ_C per timestep t when (a) $SD_{t_0} = 12.7$ m, (b) $SD_{t_0} = 101.60$ m, and (c) $SD_{t_0} = 203.20$ m. The $\times$ and $*$ represent the timesteps of the first and minimum obstacle detection, respectively.

The robustness of the agent’s decision-making against dynamic safety domain in terms of the robustness metrics for path following and collision avoidance $RM_{PF,\times}$ and $RM_{CA,*}$, respectively, is presented in Table 6.14 and Figure 6.9. Specifically, the robustness metrics are measured within and outside the trained safety domain envelope, until the robustness thresholds are violated. It is worth noting that the maximum cross-track errors $|e_{XT,OS,max}|$ are measured as an indication of the expected maximum path deviation and maximum manoeuvre for the respective robustness metrics. It is noted that the robustness threshold for path following is compliant until when $SD_{t_0} = 241.30$ m, which is an increase of 18.9% from its maximum trained value. It can be derived that the agent’s decision-making for path following and collision avoidance is robust against dynamic safety domain, due to the agent’s ability to generalise its sophisticated decision-making of conducting bigger evasive manoeuvres when the safety domain is bigger. This is particularly pivotal considering that bigger safety domain reflects higher probability of failure of the CAS and the decision-making agent conducts safer evasive manoeuvres from the detected obstacles.

Table 6.14 Robustness metrics of the agent against dynamic safety domain SD .

SD_{t_0} (m)	SD_{t_τ} (m)	$RM_{PF,\times}$ (m)	$RM_{CA,*}$ (m)
12.70	16.65	3.60	100.70
50.80	66.64	2.45	133.97
88.90	116.74	0.35	168.38
127.00	166.93	1.43	204.49
165.10	217.32	2.46	238.70
203.20	267.73	2.80	269.79
241.30	319.64	13.12	292.69

**Figure 6.9** Robustness of the agent's decision-making against dynamic safety domain SD in terms of the (a) robustness metric for path following $RM_{PF,\times}$ and (b) robustness metric for collision avoidance $RM_{CA,*}$.

6.3 Case Study 3

6.3.1 DRL-Based Agent Training

The training performance of the agent in terms of the return per episode is presented in Figure 6.10. It is noted that the return convergences to a local maximum approximately from episode 4200, as indicated by its moving median, which denotes that the agent consistently maximises the return in each episode. The training is terminated at episode 4462, which constitutes a total of 1,883,669 steps and approximately 34 hours of training. The minimum and maximum values of the training performance metrics derived during the training and their respective moving medians at the end of the training are presented in Table 6.15. The position y_{obs} generated randomly during the training in terms of its distribution is presented in Figure 6.11. The mean value of its distribution $\bar{y}_{obs} = 2,000.1$ m denotes that the

agent is trained effectively from diverse scenarios of uniformly distributed random values.

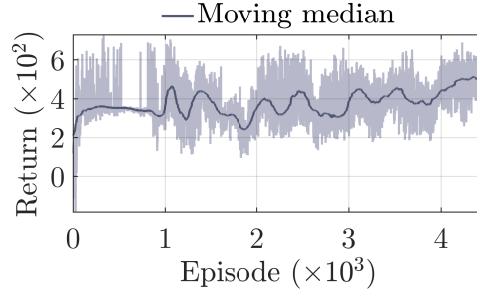


Figure 6.10 Return per episode during the training of agent. The sliding windows of their respective moving medians are 150 episodes.

Table 6.15 Training performance metrics during the training of agent.

Return _{min}	Return _{max}	Moving Median ¹
-183.86	728.52	496.89

¹ At episode 4462. Sliding window of 150 episodes.

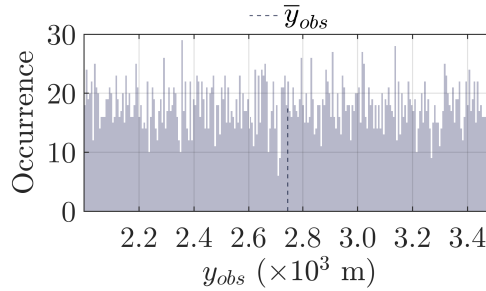


Figure 6.11 Distributions of the position y_{obs} generated during the training of agent. The number of bins for each histogram is 250.

6.3.2 Decision-Making Agent's Robustness Verification

The trained agent is simulated in various scenarios within the trained envelope, but for brevity, only the results pertaining to $x_{obs} = 2500$ m and $y_{obs} = 2500$ m is presented. The agent's decision-making in terms of the conducted manoeuvring with coupled propeller-rudder control is presented in Figure 6.12. The actor's policy in terms of the commanded rudder angle δ_C and commanded propeller revolution n_C per timestep t is presented in Figure 6.13. It is noted that the agent concurrently controls both the rudder and propeller by outputting nominal commands during the path following and path recovery manoeuvres, whereas it outputs different commands during the evasive manoeuvre. Specifically, the agent increases the propeller revolution during

the evasive manoeuvre, as indicated by the timesteps $\times$ and $*$, despite the modelling of the propeller revolution reward function that maximises its reward when close to the nominal propeller revolution. It is worth noting that sharper evasive manoeuvres can be achieved with the increase of propeller revolution [300]. This lends credence to the notion that the agent has learned a sophisticated control strategy outside of the pre-settled control strategies to counteract the loss of speed and assist a sharper manoeuvre during critically proximate obstacles.

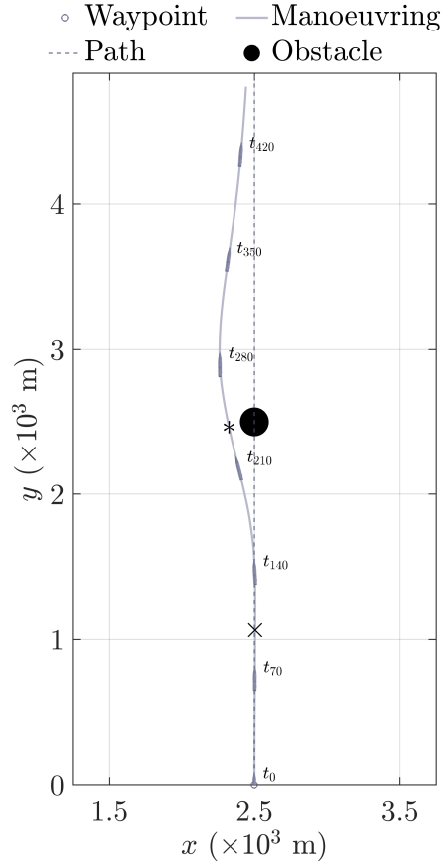


Figure 6.12 Decision-making of the agent in terms of the conducted manoeuvring with propeller-rudder coupled control. The position of the OS is plotted every 70 s. The $\times$ and $*$ represent the timesteps of the first and minimum obstacle detection, respectively.

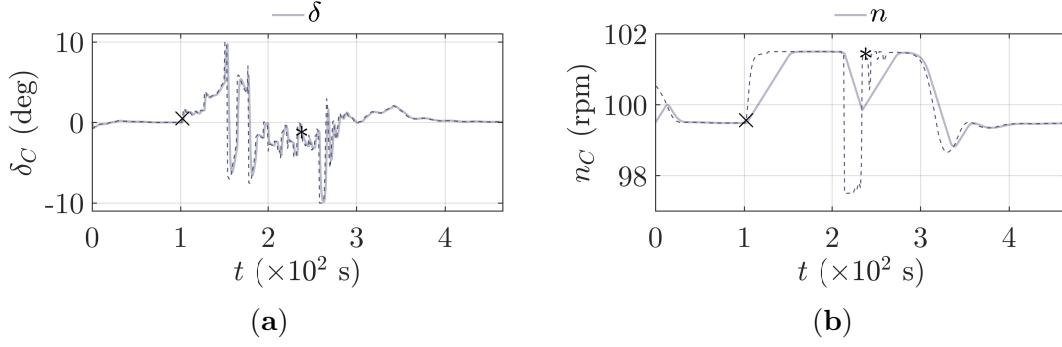


Figure 6.13 Actor's policy of the agent in terms of the commanded rudder angle δ_C and commanded propeller revolution n_C per timestep t . The $\times$ and $*$ represent the timesteps of the first and minimum obstacle detection, respectively.

The robustness of the agent's decision-making with propeller-rudder coupled control in terms of the robustness metrics for collision avoidance $RM_{CA,*}$ is presented in Figure 6.15. Specifically, the robustness metrics are measured within and outside the trained obstacle size, until the robustness threshold is violated. It is noted that the robustness threshold for collision avoidance is compliant until when the obstacle size is increased by 210% from its trained value. It can be derived that the agent's decision-making for collision avoidance is robust, due to the agent's ability to generalise its sophisticated decision-making of concurrently controlling the propeller and rudder amidst different obstacle sizes.

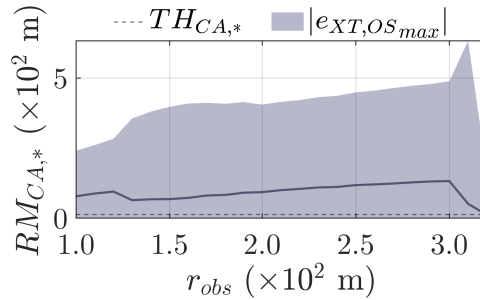


Figure 6.14 Robustness of the agent's decision-making with propeller-rudder coupled control in terms of the robustness metric for collision avoidance $RM_{CA,*}$.

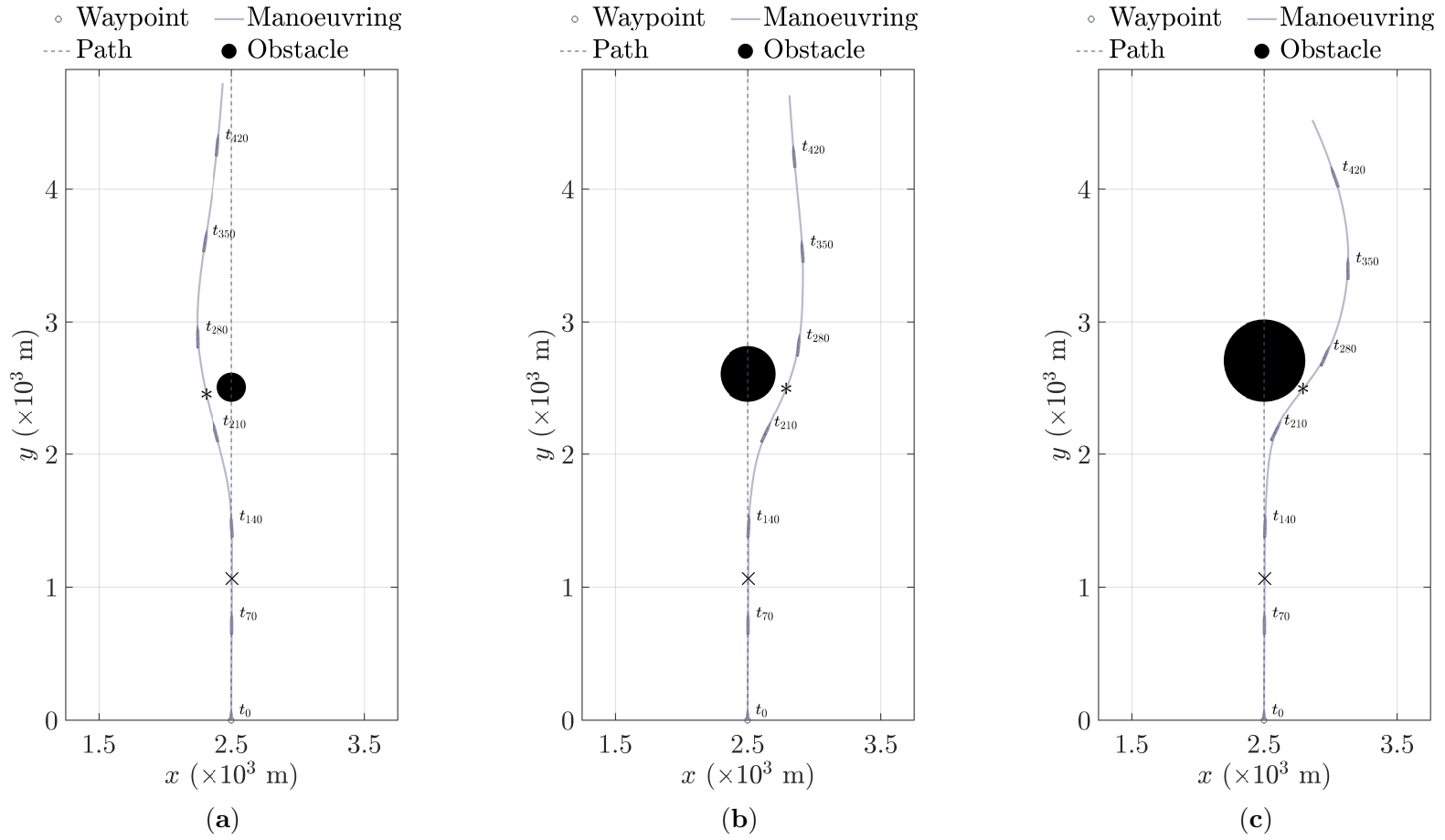


Figure 6.15 Decision-making of the agent in terms of the conducted manoeuvring when obstacle size is (a) 110 m, (b) 210 m, and (c) 310 m. The position of the OS is plotted every 70 s. The $\times$ and $*$ represent the timesteps of the first and minimum obstacle detection, respectively.

6.4 Case Study 4

6.4.1 DRL-Based Agent Training

The training performance of the agent_A in terms of the return per episode, actor loss per step, and critic loss per step is presented in Figure 6.16. It is noted that the return converges to a local maximum approximately from episode 4800, as indicated by its moving median, with further reduction of its variance from episode 5500, which denotes that the agent consistently maximises the return in each episode. The actor loss converges to a local minimum from step 2.25×10^6 , as indicated by its moving median, which denotes that the actor converges to a stable policy. In contrast, the critic loss diverges from a local minimum from step 1.75×10^6 , as indicated by its moving median, with a general increase of its variance due to exploding values, which suggests that the critic does not converge to a stable estimation of the expected return. However, despite this instability, the critic loss exhibits a downward trend potentially towards a local minimum from step 2.3×10^6 , as indicated by its moving median, which is in alignment with the overall convergence trends of the other training performance metrics.

The training is terminated at episode 5820, which constitutes a total of 2,529,998 steps and approximately 44 hours of training. The minimum and maximum values of the training performance metrics derived during the training and their respective moving medians at the end of the training are presented in Table 6.16. The noise variances σ^2 and vertical positions y_{obs} generated randomly during the training in terms of their distributions are presented in Figure 6.17. The mean values of their distributions $\overline{\sigma^2} = 12.40 \text{ m}^2$ and $\bar{y}_{\text{obs}} = 2745.70 \text{ m}$ denote that the agent is trained effectively from diverse scenarios of uniformly distributed random values.

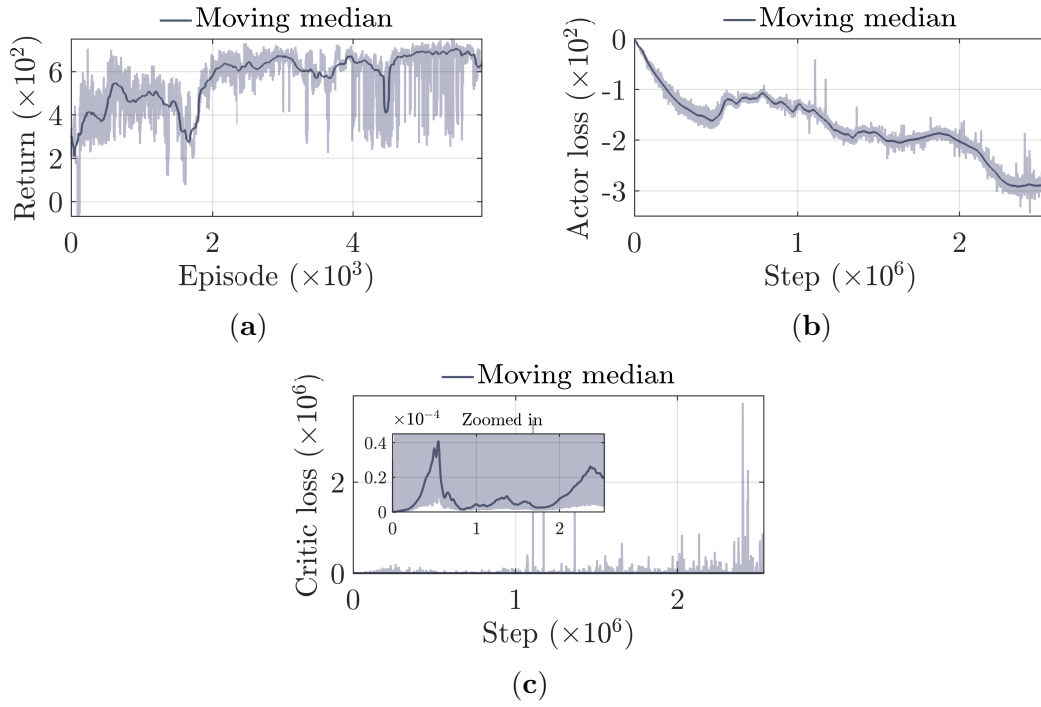


Figure 6.16 (a) Return per episode, (b) actor loss per step, and (c) critic loss per step during the training of agent_A. The sliding windows of their respective moving medians are 150 episodes and 25,000 steps.

Table 6.16 Training performance metrics during the training of agent_A.

Return _{A,min}	Return _{A,max}	Moving Median _A ¹
-67.42	749.72	633.84
Actor loss _{A,min}	Actor loss _{A,max}	Moving Median _A ²
-344.62	-0.45	-288.36
Critic loss _{A,min}	Critic loss _{A,max}	Moving median _A ²
2.10×10^{-3}	3,750,911	19.39

¹ At episode 5820. Sliding window of 150 episodes. ² At episode 5820. Sliding window of 25,000 steps.

The exploding values of the critic loss can be attributed to the poor observations normalisation or issues related to numerical differentiation. Specifically, some observations are found to explode during the training, such as the $\ddot{e}_{XT}$, as presented in Figure 6.18. Retraining the agent_A, while using hard limiters on these observations, improves the convergence of the critic loss. Similar effects can be derived by adjusting the timestep, using a different solver, or employing other differentiation techniques, but potentially at the expense of longer simulation periods. However, this is presented only as a critical discussion on the effect of exploding observations on the training performance. The initial settings are maintained as the optimisation

of the observations normalisation and numerical differentiation exceed the scope of this study.

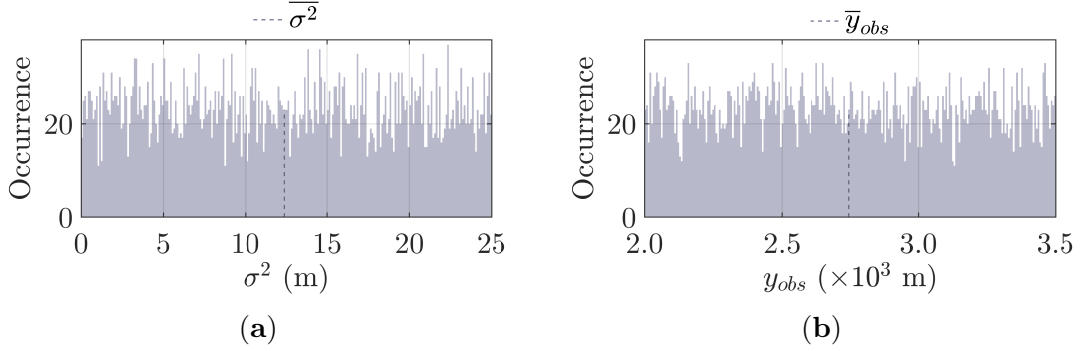


Figure 6.17 Distributions of (a) random noise variances σ^2 and (b) random vertical positions y_{obs} generated during the training of agent_A. The number of bins for each histogram is 250.

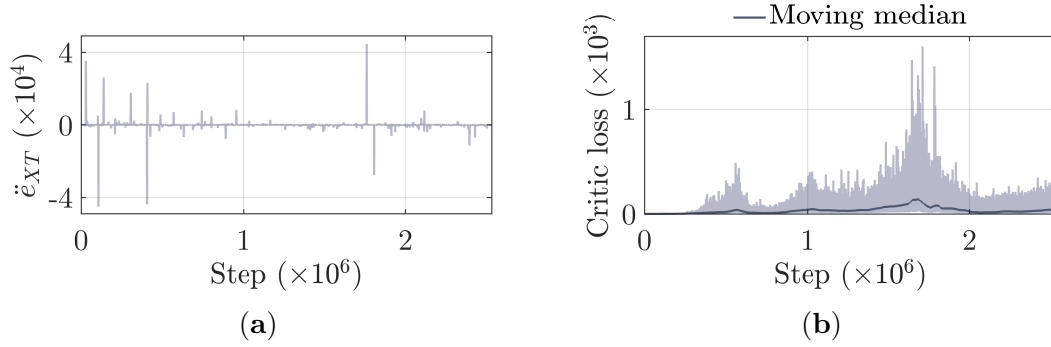


Figure 6.18 (a) Exploding values of the $\ddot{e}_{XT}$ observation during the training of agent_A. (b) Critic loss per step during the training of agent_A using hard limiters on the exploding observations. The sliding window of the moving median is 25,000 steps.

6.4.2 Decision-Making Agent's Robustness Verification

The trained agent_A is simulated in various scenarios within the trained noise levels envelope, but for brevity, only the results pertaining to a single obstacle position on the middle of the path $x_{obs} = 2500$ m and $y_{obs} = 2500$ m and minimum and maximum noise variances $\sigma^2 = 0$ m² and $\sigma^2 = 25$ m², respectively, are presented. The agent's decision-making in terms of the conducted manoeuvring in each scenario is presented in Figure 6.19. It is worth noting that the same random seeds are used for the reproducibility of the generated noises in the LIDAR measurements and consistency of the results.

The returns that the agent accumulates are 695.72 when $\sigma^2 = 25$ m² and 708.32 when $\sigma^2 = 0$ m², which suggest that the agent's decision-making is different in

each scenario. Specifically, the decomposition of each return to its reward functions, as presented prior in Equation (5.8), indicates that R_1 corresponds to 74.9% of the difference from $\sigma^2 = 25 \text{ m}^2$ to $\sigma^2 = 0 \text{ m}^2$, followed by the R_5 , R_2 , and R_3 that correspond to -39.9% , 35.4% , and 29.6% , respectively. This implies that the higher accumulated return when the noise variance is lower is due to the agent's decision-making exploiting more the path following, nominal navigation, and rudder control rewards against the collision avoidance reward, which is manifested as smaller evasive manoeuvres. The opposite applies when the noise variance is higher resulting in larger evasive manoeuvres. This lends credence to the notion of the agent's sophisticated decision-making, capable of prioritising safety over efficiency depending on the noise variance, which is desirable from safety perspective considering the increased uncertainties under higher noise variances and the limited temporal and spatial margins for error during reactive collision avoidance.

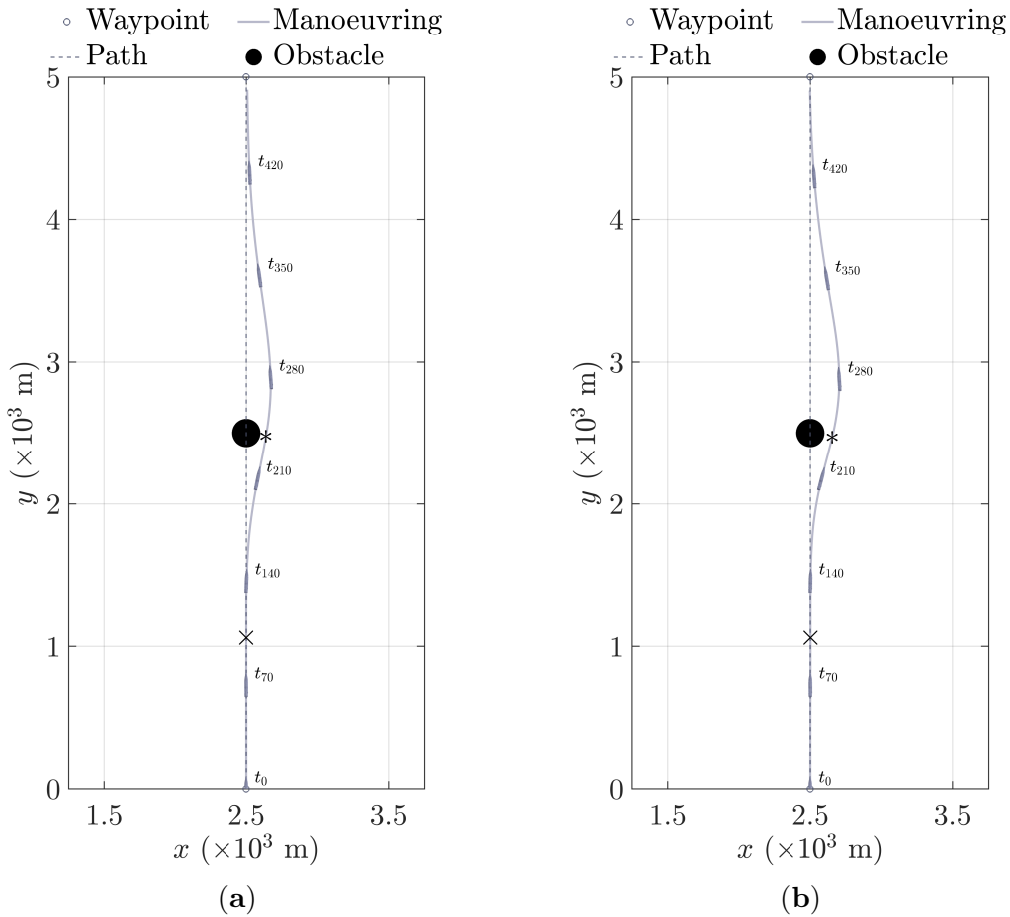


Figure 6.19 Decision-making of the agent_A in terms of the conducted manoeuvring when (a) $\sigma^2 = 0 \text{ m}^2$ and (b) $\sigma^2 = 25 \text{ m}^2$. The position of the OS is plotted every 70 s. The $\times$ and $*$ represent the timesteps of the first and minimum obstacle detection, respectively.

The actor's policy in terms of the commanded rudder angle δ_C per timestep t

is presented in Figure 6.20. It is noted that the commanded rudder angles become more erratic when $\sigma^2 = 25 \text{ m}^2$, potentially due to the uncertainties of the noisy measurements. For instance, a LIDAR measurement less than its maximum detecting range clearly indicates a detection of an obstacle when $\sigma^2 = 0 \text{ m}^2$, whereas the distinction between noisy LIDAR measurements and detection of an obstacle becomes more uncertain when $\sigma^2 = 25 \text{ m}^2$. However, despite this uncertainty, the actor deflects the rudder angle to initiate an evasive manoeuvre only after the first obstacle detection, as indicated by the timesteps $\times$. This can be attributed to the great feature extraction capabilities of DNNs, enabling them to discern genuine obstacle detections amidst the noisy measurements.

In addition, it is noted that the actor’s policy is inherently different in each scenario, not only in terms of its erratic output. Specifically, the absolute area under the commanded rudder angles is increased by 25.2% when $\sigma^2 = 25 \text{ m}^2$ compared to when $\sigma^2 = 0 \text{ m}^2$, where the normalised area per timestep for the evasive manoeuvre corresponds to 55.3% of the difference, followed by the path following and path recovery manoeuvres that correspond to 28.7% and 16.0%, respectively. In addition, the magnitude of the commanded rudder angles at the minimum obstacle detections are 7.76 deg when $\sigma^2 = 25 \text{ m}^2$ and 5.97 deg $\sigma^2 = 0 \text{ m}^2$, as indicated by the timesteps $*$. It can be derived that the prior finding on the agent’s sophisticated decision-making conducting different evasive manoeuvres depending on the noise variance is attributed to the difference between the commanded rudder angles, which is particularly evident during the evasive manoeuvres. This lends credence to the notion of the actor’s expressiveness, stemming from its policy’s ability to capture the complexity and richness across different noise variances and provide a different output, which is desirable considering the dynamic operating conditions affecting the stochastic nature of noise differently.

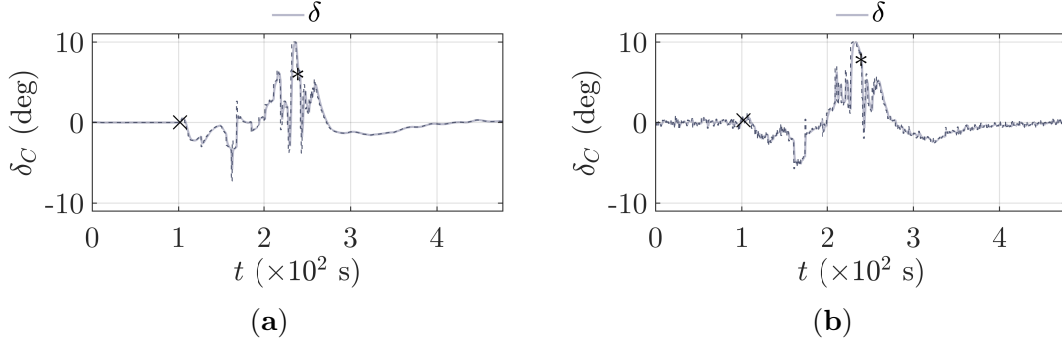


Figure 6.20 Actor's policy of the agent_A in terms of the commanded rudder angle δ_C per timestep t when (a) $\sigma^2 = 0 \text{ m}^2$ and (b) $\sigma^2 = 25 \text{ m}^2$. The $\times$ and $*$ represent the timesteps of the first and minimum obstacle detection, respectively.

The critic's estimation in terms of the expected return Q -value per return is presented in Figure 6.21. It is worth noting that despite the role of the critic's estimation on the actor's policy improvement taking place only during the training of the agent, the investigation of the Q -value can give meaningful insight to interpret the learned policy, as discussed herein. It is noted that the Q -values are more closely spread throughout the diagonal of the optimal estimation when $\sigma^2 = 0 \text{ m}^2$ compared to when $\sigma^2 = 25 \text{ m}^2$, which suggests that the critic makes more accurate estimations consistently when the noise variance is lower. Specifically, the respective errors between the Q -value and actual return at the first and minimum obstacle detections are -156.82 and -49.92 , respectively, when $\sigma^2 = 25 \text{ m}^2$ and -96.88 and -25.43 , respectively, when $\sigma^2 = 0 \text{ m}^2$, as indicated by the timesteps $\times$ and $*$, respectively.

In addition, it is noted that the estimations are inherently different in each scenario, not only in terms of its accuracy. Specifically, the absolute area under the Q -values is reduced by -18.4% when $\sigma^2 = 25 \text{ m}^2$ compared to when $\sigma^2 = 0 \text{ m}^2$, where the normalised area per timestep for the path following manoeuvre corresponds to 57.2% of the difference, followed by the evasive manoeuvre and path recovery manoeuvre that correspond to 39.5% and 3.3% , respectively. The difference between the Q -values that is particularly evident during the path following manoeuvre even when no obstacle detection has occurred, suggests that the critic exhibits a general trend towards conservatism over optimism when the noise variance is higher. Considering that the reward functions remain unchanged regardless of the noise variance, the critic's conservatism can be attributed to the uncertainties of triggering the collision criterion. For instance, given equal obstacle positions and evasive manoeuvres in

two episodes during the agent's training, the probability of the collision criterion being triggered is higher in the episode with the higher noise variance, which if triggered, leads to the automatic termination of the episode and consequently to the accumulation of a lower return.

To compensate that, the critic learns to underestimate its expected return when the noise variance is higher, which encourages the actor not to exploit the current policy but rather to explore. Exploitation of the policy corresponds to increased tendency towards maximising the return manifested as smaller evasive manoeuvres according to the prior finding on the agent's decision-making over the rewards. Exploration of the policy corresponds to increased tendency towards exploring different commanded rudder angles manifested as larger evasive manoeuvres, which verifies the prior finding on the actor's learned policy to output larger commanded rudder angles when the noise variance is higher. This lends credence to the notion of the critic's adaptability, stemming from its ability to adjust its estimation of the expected return depending on the noise variance, which is desirable from safety perspective considering conservatism during higher collision risk.

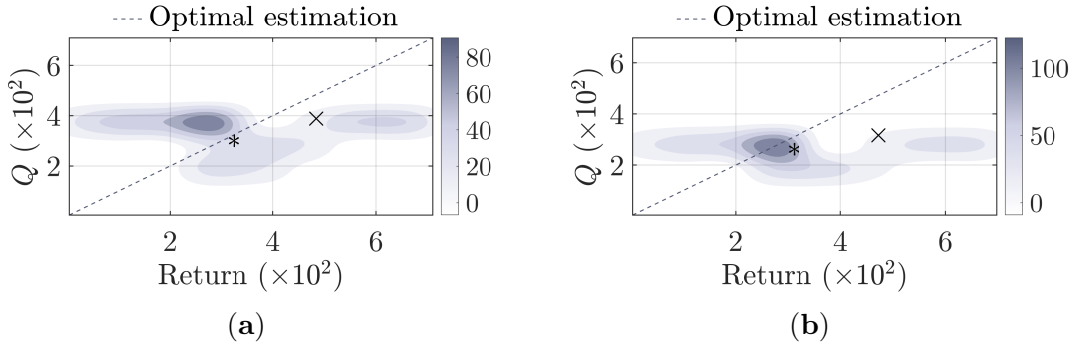


Figure 6.21 Critic's estimation of the agent_A in terms of the expected return Q -value per return when (a) $\sigma^2 = 0 \text{ m}^2$ and (b) $\sigma^2 = 25 \text{ m}^2$. The colour bar of each density map represents the density values, where darker colours indicate higher concentrations and lighter colours indicate lower concentrations. The $\times$ and $*$ represent the timesteps of the first and minimum obstacle detections, respectively.

Sensitivity analysis of the trained agent_A's actor and critic to noise variance is conducted, considering the prior findings suggesting its impact on their output. Specifically, the noise variance σ^2 affects the noise level of the LIDAR measurements observation d and the value of the noise variance observation $\mathcal{N}$, as presented prior in Equation (5.9). To investigate the sensitivity to each of these observations, they are decoupled by assigning two independent noise variances as σ_d^2 and $\sigma_{\mathcal{N}}^2$, respectively.

The sensitivity is quantified by measuring the errors of the actor's and critic's outputs in terms of the commanded rudder angles and expected returns e_{δ_C} and e_Q , respectively, using as baselines for the analysis their original outputs.

The agent is simulated in various scenarios investigating different combinations of noise variances $\sigma_d^2 = [0, 25] \text{ m}^2$ and $\sigma_{\mathcal{N}}^2 = [0, 25] \text{ m}^2$, but for brevity only the results pertaining to their minimum and maximum values are discussed. The actor's and critic's outputs when $\sigma_d^2 = 25 \text{ m}^2$ and $\sigma_{\mathcal{N}}^2 = 0 \text{ m}^2$ and when $\sigma_d^2 = 0 \text{ m}^2$ and $\sigma_{\mathcal{N}}^2 = 25 \text{ m}^2$ are presented in Figure 6.22 and Figure 6.23. Qualitative evaluation suggests that their outputs resemble the original outputs, as presented prior in Figure 6.20 and Figure 6.21, where the similarities are found only when the noise variance $\sigma_{\mathcal{N}}^2$ is equal to the σ_d^2 , regardless of the σ_d^2 . The erratic output is introduced only when $\sigma_d^2 = 25 \text{ m}^2$, which suggests that the erratic output is intrinsic to the LIDAR measurements observation d and not to the noise variance observation $\mathcal{N}$.

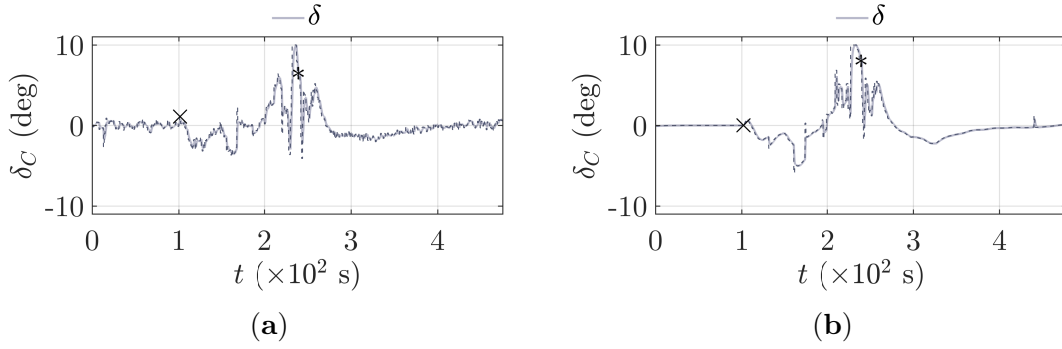


Figure 6.22 Actor's policy of the agent_A in terms of the commanded rudder angle δ_C per timestep t when (a) $\sigma_d^2 = 25 \text{ m}^2$ and $\sigma_{\mathcal{N}}^2 = 0 \text{ m}^2$ and (b) $\sigma_d^2 = 0 \text{ m}^2$ and $\sigma_{\mathcal{N}}^2 = 25 \text{ m}^2$. The $\times$ and $*$ represent the timesteps of the first and minimum obstacle detection, respectively.

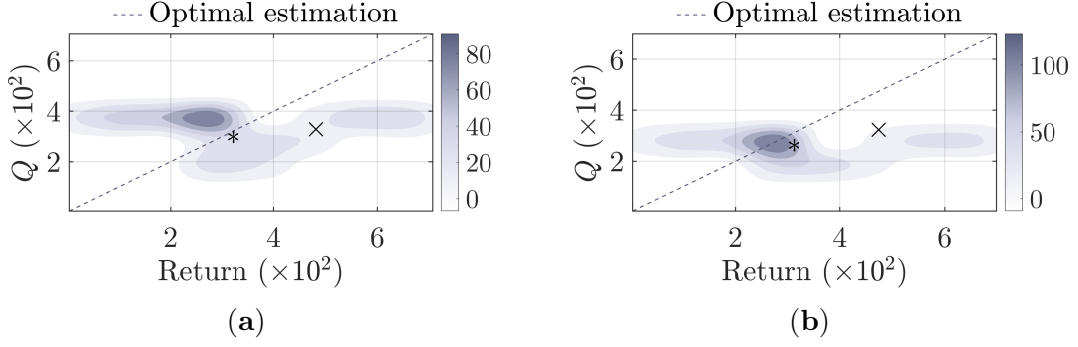
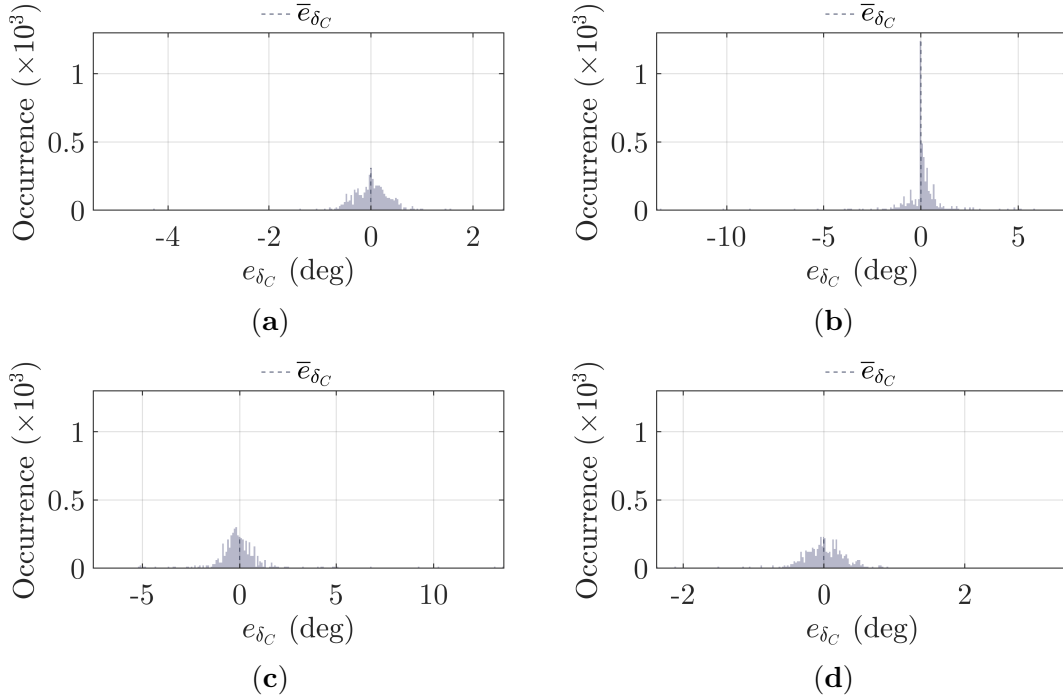


Figure 6.23 Critic's estimation of the agent_A in terms of the expected return Q -value per return when (a) $\sigma_d^2 = 25 \text{ m}^2$ and $\sigma_{\mathcal{N}}^2 = 0 \text{ m}^2$ and (b) $\sigma_d^2 = 0 \text{ m}^2$ and $\sigma_{\mathcal{N}}^2 = 25 \text{ m}^2$. The colour bar of each density map represents the density values, where darker colours indicate higher concentrations and lighter colours indicate lower concentrations. The $\times$ and $*$ represent the timesteps of the first and minimum obstacle detection, respectively.

The results of the sensitivity analysis in terms of the distributions of the actor's and critic's errors e_{δ_C} and e_Q , respectively, are presented in Table 6.17, Figures 6.24 and 6.25. It is noted that the actor's error e_{δ_C} exhibits major difference in the standard deviation values $\sigma_{e_{\delta_C}}$, which denote variability between the commanded rudder angles similar to the prior finding on the actor's output. The critic's error e_Q exhibits major difference in the mean values $\bar{e}_Q$, which denote central tendency deviation between the expected returns similar to the prior findings on the critic's output. Specifically, the differences are evident during the variations of the noise variance $\sigma_{\mathcal{N}}^2$ with the standard deviation and mean values of the actor's and critic's errors $\sigma_{e_{\delta_C}}$ and $\bar{e}_Q$ differing up to 347.2% and $-164,700.0\%$, respectively, compared to their respective values during the variations of the noise variance σ_d^2 , which denotes that both the actor and critic are significantly more sensitive to the noise variance $\sigma_{\mathcal{N}}^2$. This lends credence to the notion that the noise variance observation $\mathcal{N}$ is the most critical one, to which the sophisticated decision-making of the agent, expressiveness of the actor's policy, and adaptability of the critic's estimation can be attributed. The practical implications of this notion is the importance of signal processing techniques not only in filtering out the noise, but also in accurately estimating the noise variance value from the noisy measurements in order to guarantee the expected decision-making from the agent. It provides a way forward towards a more effective and efficient integration between signal processing and decision-making techniques, which is pivotal to ensuring safety of autonomous systems.

Table 6.17 Sensitivity analysis of the agent_A's actor and critic to different noise variance combinations σ_d^2 and σ_N^2 .

σ^2 (m ²)	σ_d^2 (m ²)	σ_N^2 (m ²)	$\bar{e}_{\delta_C}$ (deg)	$\sigma_{e_{\delta_C}}$ (deg)	$e_{\delta_C, \min}$ (deg)	$e_{\delta_C, \max}$ (deg)
0	25	0	-3.95×10^3	0.48	-5.47	2.60
0	0	25	3.35×10^3	1.53	-13.60	7.54
25	25	0	-7.23×10^3	1.61	-7.52	13.60
25	0	25	1.08×10^3	0.36	-2.38	3.46
σ^2 (m ²)	σ_d^2 (m ²)	σ_N^2 (m ²)	$\bar{e}_Q$	σ_{e_Q}	$e_{Q, \min}$	$e_{Q, \max}$
0	25	0	4.26	16.41	-25.90	109.03
0	0	25	53.72	17.96	-26.14	80.98
25	25	0	-49.38	21.05	-87.22	59.03
25	0	25	0.03	2.37	-10.49	42.22

**Figure 6.24** Distribution of the actor's output error of the agent_A in terms of the commanded rudder angles e_{δ_C} when (a) $\sigma_d^2 = 25$ m² and $\sigma_N^2 = 0$ m² from baseline $\sigma^2 = 0$ m², (b) $\sigma_d^2 = 0$ m² and $\sigma_N^2 = 25$ m² from baseline $\sigma^2 = 0$ m², (c) $\sigma_d^2 = 25$ m² and $\sigma_N^2 = 0$ m² from baseline $\sigma^2 = 25$ m², and (d) $\sigma_d^2 = 0$ m² and $\sigma_N^2 = 25$ m² from baseline $\sigma^2 = 25$ m². The number of bins for each histogram is 250.

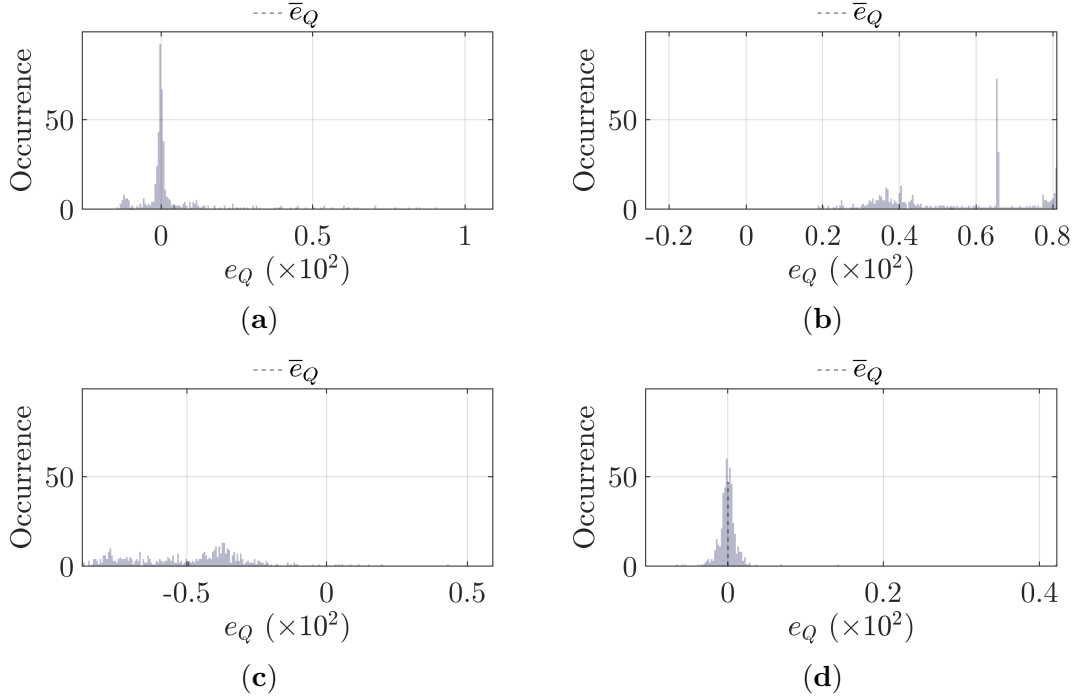


Figure 6.25 Distribution of the critic's output error of the agent_A in terms of the expected returns e_Q when (a) $\sigma_d^2 = 25 \text{ m}^2$ and $\sigma_{\mathcal{N}}^2 = 0 \text{ m}^2$ from baseline $\sigma^2 = 0 \text{ m}^2$, (b) $\sigma_d^2 = 0 \text{ m}^2$ and $\sigma_{\mathcal{N}}^2 = 25 \text{ m}^2$ from baseline $\sigma^2 = 0 \text{ m}^2$, (c) $\sigma_d^2 = 25 \text{ m}^2$ and $\sigma_{\mathcal{N}}^2 = 0 \text{ m}^2$ from baseline $\sigma^2 = 25 \text{ m}^2$, and (d) $\sigma_d^2 = 0 \text{ m}^2$ and $\sigma_{\mathcal{N}}^2 = 25 \text{ m}^2$ from baseline $\sigma^2 = 25 \text{ m}^2$. The number of bins for each histogram is 250.

The robustness of the agent_A's decision-making against noise variances in terms of the robustness metrics for path following and collision avoidance $RM_{PF,\times}$ and $RM_{CA,*}$, respectively, is presented in Table 6.18 and Figure 6.27. Specifically, the robustness metrics are measured within and outside the trained noise variance envelope, until the robustness thresholds are violated. It is worth noting that the maximum cross-track errors $|e_{XT,\max}|$ are measured in the absence and presence of the obstacle as an indication of the expected maximum path deviation and maximum manoeuvre for the respective robustness metrics. It is noted that the robustness threshold for path following is compliant until when $\sigma^2 = 58 \text{ m}^2$, which is an increase of 132% from its maximum trained value. The agent's decision-making in terms of the conducted manoeuvring when $\sigma^2 = 25 \text{ m}^2$ and $\sigma^2 = 58 \text{ m}^2$ is presented in Figure 6.26. Specifically, the robustness metric for path following $RM_{PF,\times}$ decreases approximately from $\sigma^2 = 40 \text{ m}^2$ due to early path deviation prior to obstacle detection. However, it is worth noting that the robustness thresholds for path following as $B/2$ is already a stringent requirement considering that typical XTLs are of a few NM [273].

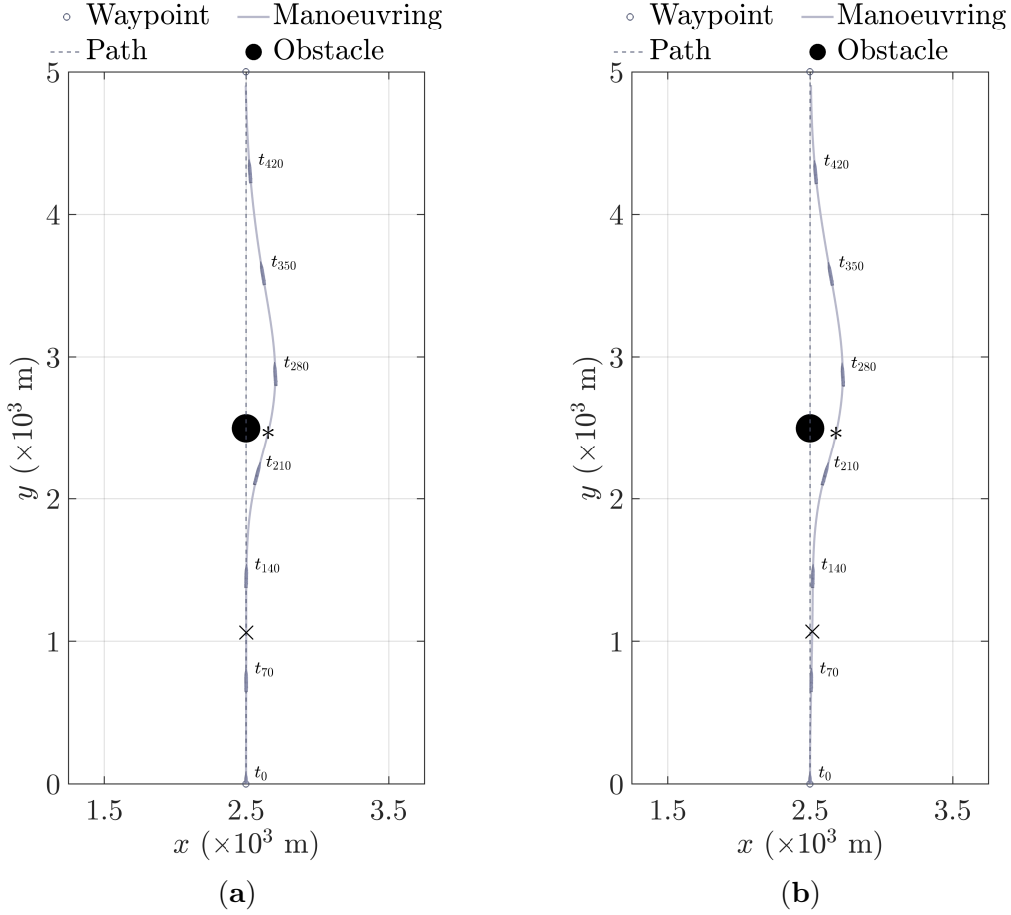
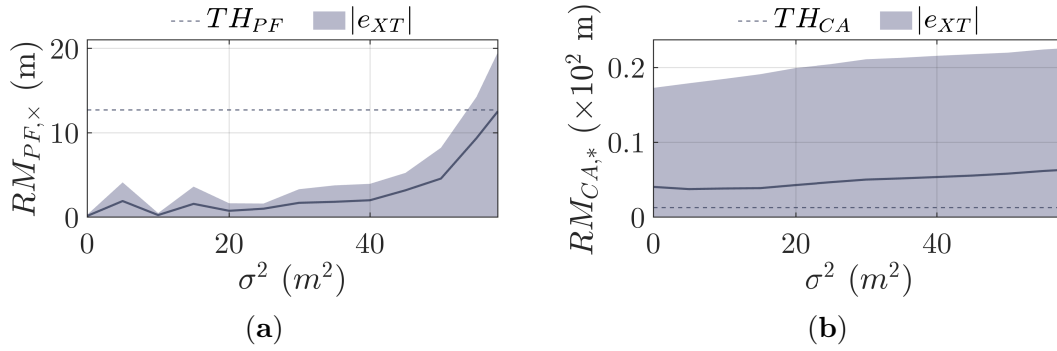


Figure 6.26 Decision-making of the agent_A in terms of the conducted manoeuvring when (a) $\sigma^2 = 25$ m² and (b) $\sigma^2 = 58$ m². The position of the OS is plotted every 70 s. The $\times$ and $*$ represent the timesteps of the first and minimum obstacle detection, respectively.

The robustness threshold for collision avoidance is compliant even when the threshold for path following is violated. Specifically, the robustness metric for collision avoidance $RM_{CA,*}$ exhibits an increasing trend, where it is increased by 15.5% when $\sigma^2 = 25$ m² and by 52.6% when $\sigma^2 = 58$ m² compared to when $\sigma^2 = 0$ m². It is worth noting that the increase of the robustness metric for collision avoidance is noted even prior to the early path deviation of the robustness metric for path following taking effect from $\sigma^2 = 40$ m². It can be derived that the agent's decision-making for path following and collision avoidance is robust against noise variances, due to the agent's ability to generalise its sophisticated decision-making of prioritising safety over efficiency across higher noise variances. This lends credence to the notion that the noise variance observation $\mathcal{N}$ continues to exhibit critical importance on the agent's decision-making even beyond the trained noise level envelope.

Table 6.18 Robustness metrics of the agent_A against noise variances σ^2 .

σ^2 (m ²)	$RM_{PF,\times,A}$ (m)	$RM_{CA,*,A}$ (m)
0	0.14	40.41
10	0.24	38.27
20	0.75	42.87
30	1.69	50.17
40	2.00	53.59
50	4.57	58.14
60	14.63	64.33

**Figure 6.27** Robustness of the agent_A's decision-making against noise variance σ^2 in terms of the (a) robustness metric for path following $RM_{PF,\times}$ and (b) robustness metric for collision avoidance $RM_{CA,*}$.

Agent_B that exhibits the same hyperparameter settings as the agent_A is trained within the same training framework, but without the noise variance observation $\mathcal{N}$, to investigate the effectiveness of the proposed methodology. The training performance of the agent_B in terms of the return per episode, actor loss per step, and critic loss per step is presented in Figure 6.28. The training of the agent_B is terminated at episode 5970, where it exhibits similar convergence trends as the agent_A. The minimum and maximum values of the training performance metrics derived during the training and their respective moving medians are presented in Table 6.19.

Table 6.19 Training performance metrics during the training of agent_B. The training performance metrics of the agent_A are presented for comparison.

Return _{A,min}	Return _{A,max}	Moving median _A ¹
-67.42	749.72	633.84
Actor loss _{A,min}	Actor loss _{A,max}	Moving median _A ³
-344.62	-0.45	-288.36
Critic loss _{A,min}	Critic loss _{A,max}	Moving median _A ³
2.10×10^{-3}	3,750,911	19.39
Return _{B,min}	Return _{B,max}	Moving median _B ²
-65.25	751.75	719.89
Actor loss _{B,min}	Actor loss _{B,max}	Moving median _B ⁴
-296.91	-0.21	-281.76
Critic loss _{B,min}	Critic loss _{B,max}	Moving median _B ⁴
1.69×10^{-3}	651,757.60	18.97

¹ At episode 5820. Sliding window of 150 episodes. ² At episode 5970. Sliding window of 150 episodes. ³ At episode 5820. Sliding window of 25,000 steps. ⁴ At episode 5970. Sliding window of 25,000 steps.

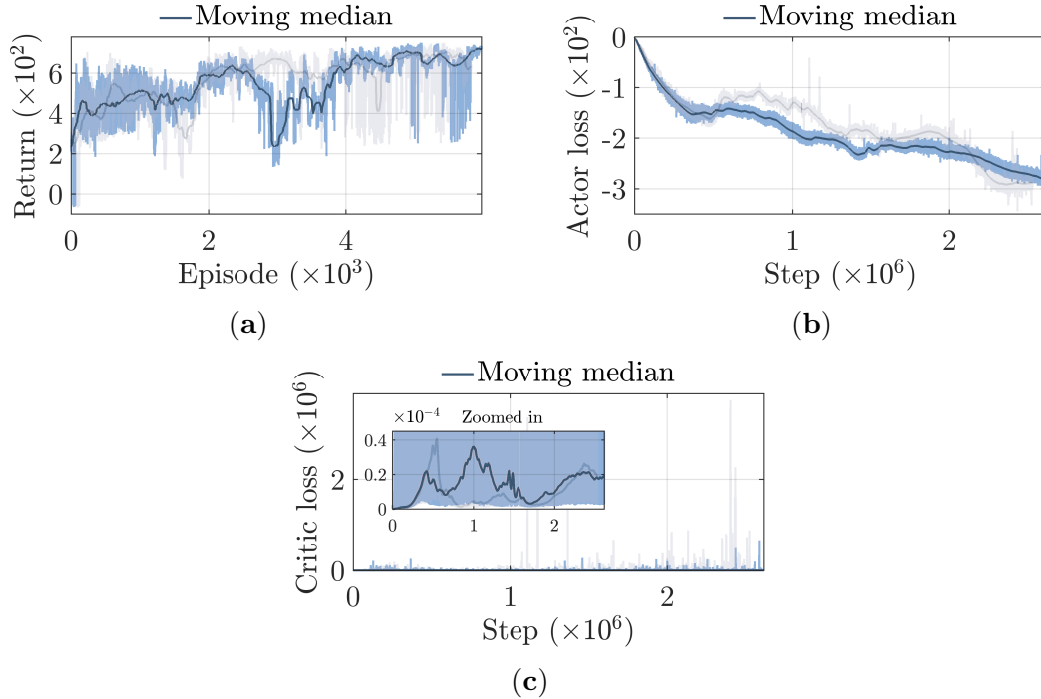


Figure 6.28 (a) Return per episode, (b) actor loss per step, and (c) critic loss per step during the training of agent_B. The sliding windows of their respective moving medians are 150 episodes and 25,000 steps. The training performance of the agent_A is presented for comparison.

The trained agent_B is simulated in the same scenarios as the agent_A, but for brevity only the results pertaining to the minimum and maximum noise variances

$\sigma^2 = 0 \text{ m}^2$ and $\sigma^2 = 25 \text{ m}^2$, respectively, are presented. The returns that the agent_B accumulates are 770.68 when $\sigma^2 = 25 \text{ m}^2$ and 771.46 when $\sigma^2 = 0 \text{ m}^2$, which suggest that the agent's decision-making is not significantly different in each scenario. The actor's policy in terms of the commanded rudder angle δ_C per timestep t is presented in Figure 6.29. The absolute area under the commanded rudder angles is increased only by 9.8% when $\sigma^2 = 25 \text{ m}^2$ compared to when $\sigma^2 = 0 \text{ m}^2$ and the magnitude of the commanded rudder angles at the minimum obstacle detections are 9.71 deg when $\sigma^2 = 25 \text{ m}^2$ and 9.70 deg when $\sigma^2 = 0 \text{ m}^2$, as indicated by the timesteps *, which suggest that the commanded rudder angles are not significantly different in each scenario, except for the erratic output noted when $\sigma^2 = 25 \text{ m}^2$.

The critic's estimation in terms of the expected return Q -value per return is presented in Figure 6.30. The absolute area under the Q -values is reduced only by -0.1% when $\sigma^2 = 25 \text{ m}^2$ compared to when $\sigma^2 = 0 \text{ m}^2$ and the errors between the estimated Q -value and actual return at the first and minimum obstacle detections are -183.83 and -117.16, respectively, when $\sigma^2 = 25 \text{ m}^2$ and -187.78 and -116.74, respectively, when $\sigma^2 = 0 \text{ m}^2$, as indicated by the timesteps $\times$ and *, respectively, which suggest that the Q -values are not significantly different in each scenario.

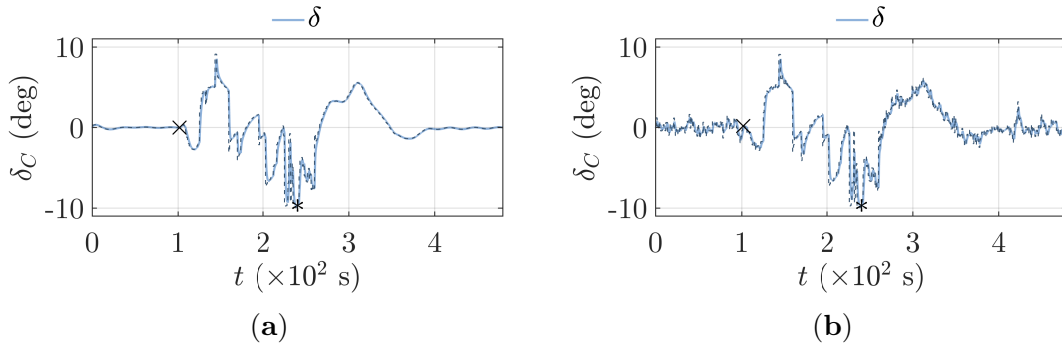


Figure 6.29 Actor's policy of the agent_B in terms of the commanded rudder angle δ_C per timestep t when (a) $\sigma^2 = 0 \text{ m}^2$ and (b) $\sigma^2 = 25 \text{ m}^2$. The $\times$ and $*$ represent the timesteps of the first and minimum obstacle detection, respectively.

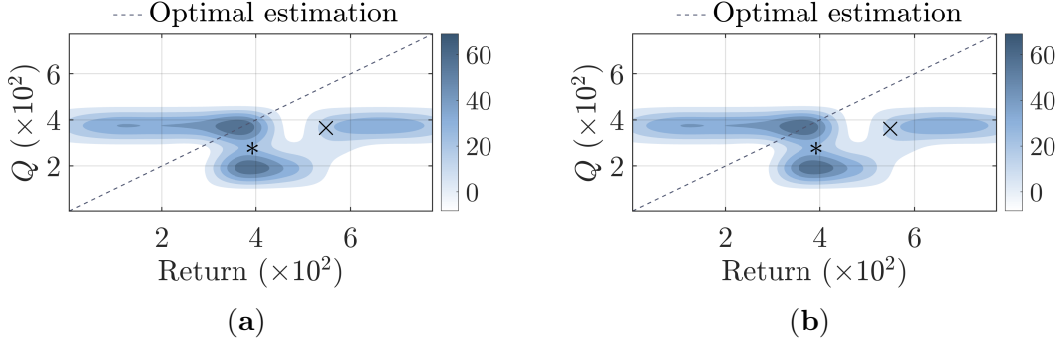
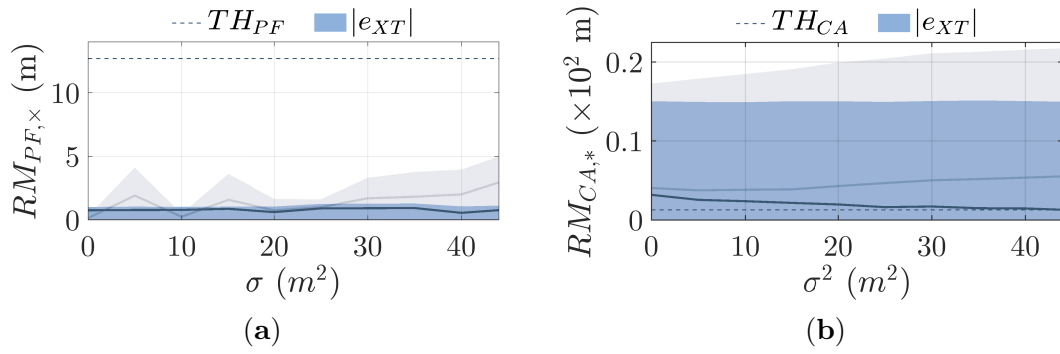


Figure 6.30 Critic's estimation of the agent_B in terms of the expected return Q -value per return when (a) $\sigma^2 = 0 \text{ m}^2$ and (b) $\sigma^2 = 25 \text{ m}^2$. The colour bar of each density map represents the density values, where darker colours indicate higher concentrations and lighter colours indicate lower concentrations. The $\times$ and $*$ represent the timesteps of the first and minimum obstacle detections, respectively.

The robustness of the agent_B's decision-making against noise variances in terms of the robustness metrics for path following and collision avoidance $RM_{PF,\times}$ and $RM_{CA,*}$, respectively, is presented in Table 6.20 and Figure 6.31. It is noted that the robustness threshold for path following is compliant even outside of the trained noise levels envelope. However, the robustness threshold for collision avoidance is violated when $\sigma^2 = 44 \text{ m}$, which is an increase of only 76% from its maximum trained value. The agent_B's decision-making in terms of the conducted manoeuvring when $\sigma^2 = 0 \text{ m}^2$ and $\sigma^2 = 44 \text{ m}^2$ is presented in Figure 6.32. The maximum manoeuvres indicated by the maximum cross-track errors $|e_{XT,\max}|$ suggest that the agent_B's decision-making across different noise variances remain the same, consequently degrading the robustness against noise variances, especially for collision avoidance. This lends credence to the notion that training the agent without the noise variance observation $\mathcal{N}$ comes at the expense of reduced sophisticated decision-making, lack of expressiveness of the actor's policy and adaptability of the critic's estimation, with worse robustness and generalisation against noise variances, highlighting the effectiveness of the proposed methodology.

Table 6.20 Robustness metrics of the agent_B against noise variances σ^2 . Robustness metrics of the agent_A are presented for comparison.

σ^2 (m^2)	$RM_{PF,\times,A}$ (m)	$RM_{CA,*,A}$ (m)	$RM_{PF,\times,B}$ (m)	$RM_{CA,*,B}$ (m)
0	0.14	40.41	0.75	31.79
10	0.24	38.27	0.78	23.70
20	0.75	42.87	0.60	19.60
30	1.69	50.17	0.91	16.99
40	2.00	53.59	0.55	14.53
50	4.57	58.14	0.65	11.44

**Figure 6.31** Robustness of the agent_B's decision-making against noise variance σ^2 in terms of the (a) robustness metric for path following $RM_{PF,\times}$ and (b) robustness metric for collision avoidance $RM_{CA,*}$. The robustness metrics of the agent_A are presented for comparison.

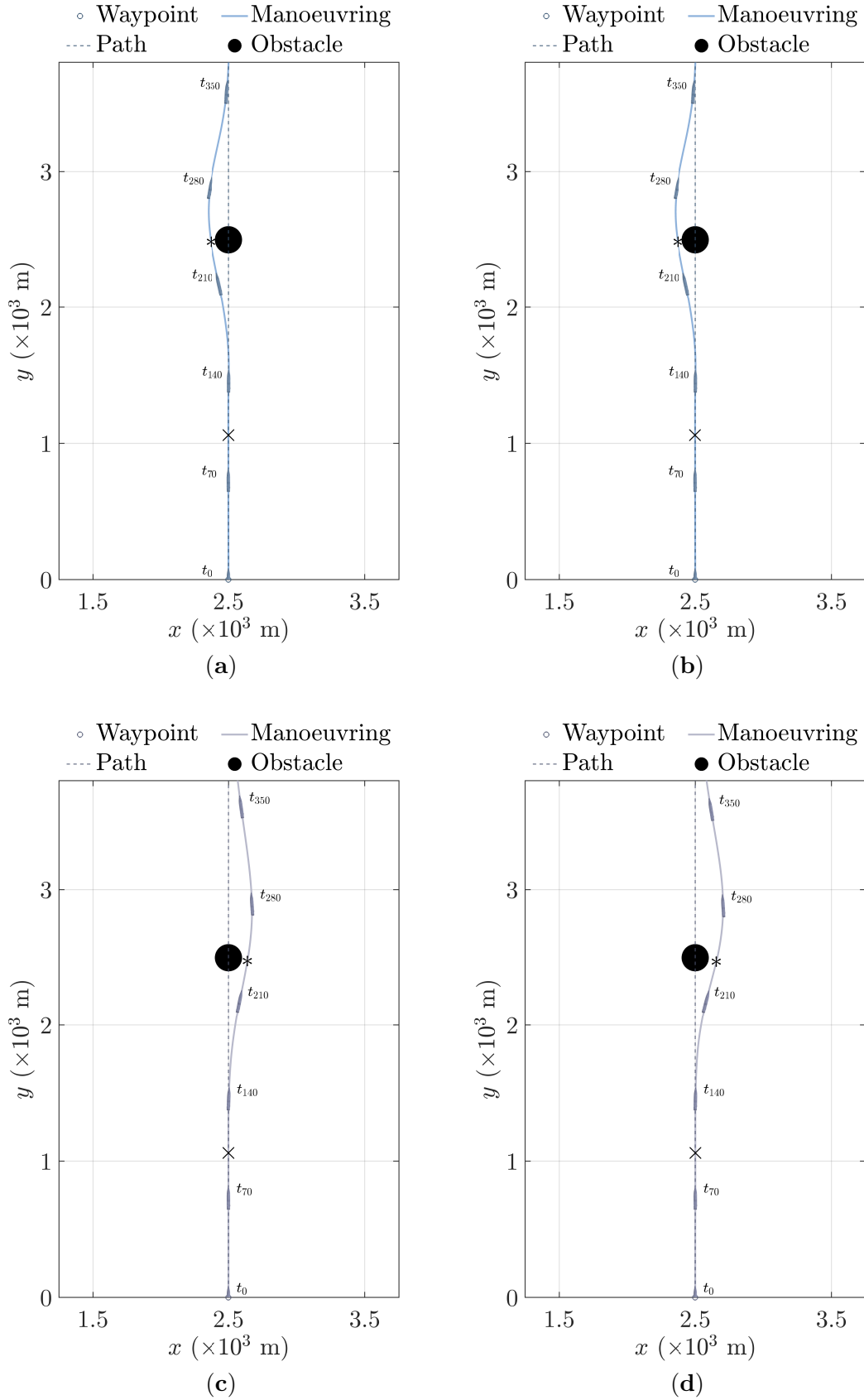


Figure 6.32 Decision-making of the agent_B in terms of the conducted manoeuvring when (a) $\sigma^2 = 0 \text{ m}^2$ and (b) $\sigma^2 = 25 \text{ m}^2$. The position of the OS is plotted every 70 s. The $\times$ and $*$ represent the timesteps of the first and minimum obstacle detection, respectively.

6.5 Case Study 5

6.5.1 DRL-Based Agent Training

The training performance of the agent in terms of the return per episode is presented in Figure 6.33. It is noted that the return convergences to a local maximum approximately from episode 2800, as indicated by its moving median, which denotes that the agent consistently maximises the return in each episode.

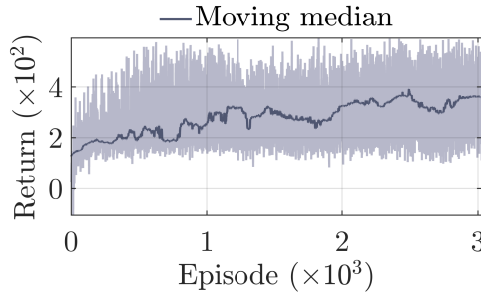


Figure 6.33 Return per episode during the training of agent. The sliding windows of their respective moving medians are 150 episodes.

The training is terminated at episode 3027, which constitutes a total of 863,897 steps and approximately 23 hours of training. The minimum and maximum values of the training performance metric derived during the training and its respective moving medians at the end of the training are presented in Table 6.21. The position x_{obs} and y_{obs} generated randomly for the static scenario and orientation ψ_{obs} generated randomly for the dynamic scenario during the training in terms of their distributions are presented in Figure 6.34. Specifically, 49.16% and 50.84% of all episodes constitute to the static and dynamic scenarios and the mean values of their distributions $\bar{x}_{\text{obs}} = 1503.5 \text{ m}^2$, $\bar{y}_{\text{obs}} = 3019.7 \text{ m}^2$, and $\bar{\psi}_{\text{obs}} = 177.92 \text{ deg}$, which denote that the agent is trained effectively from diverse scenarios of uniformly distributed random values.

Table 6.21 Training performance metric during the training of agent.

Return _{min}	Return _{max}	Moving Median ¹
-105.50	593.80	362.65

¹ At episode 3027. Sliding window of 150 episodes.

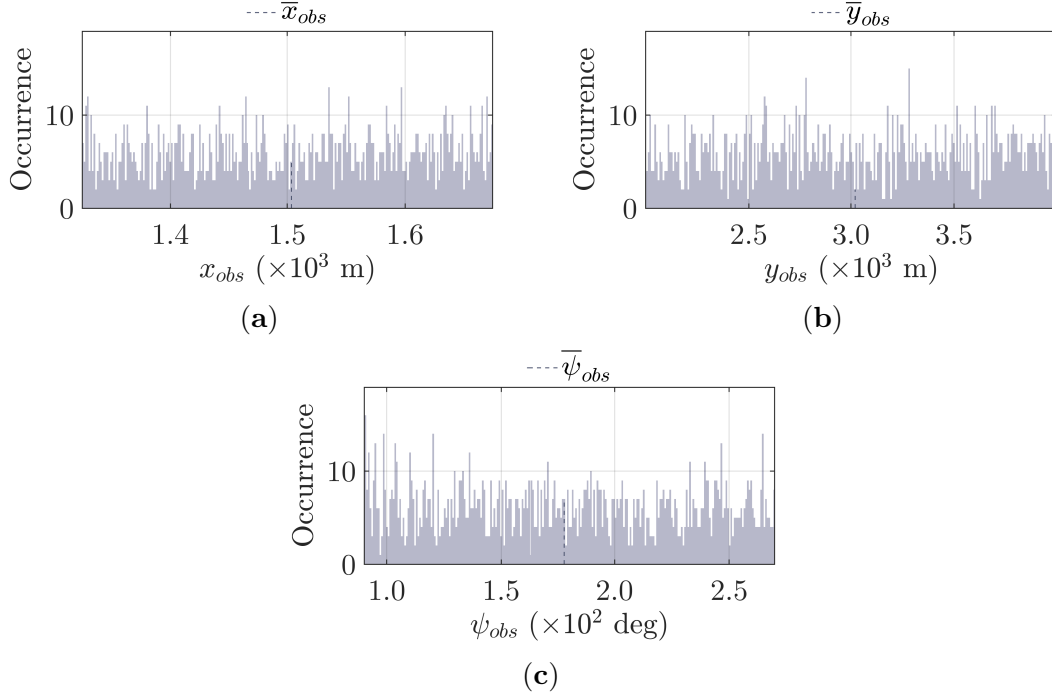


Figure 6.34 Distributions of (a) random horizontal position x_{obs} , (b) random vertical position y_{obs} , and (c) random orientation ψ_{obs} generated during the training of agent. The number of bins for each histogram is 250.

6.5.2 Decision-Making Agent's Robustness Verification

The trained agent is simulated in various scenarios within the trained envelope, but for brevity, only the results pertaining to $x_{obs} = [1587.5, 1500, 1412.5]$ m at $y_{obs} = 2000$ m that constitute to $e_{XT,obs} = [-87.5, 0, 87.5]$ m for the static scenarios and heading angles of the dynamic obstacle $\psi_{obs} = [90, 180, 270]$ deg that constitutes to relative angles of $\Theta_{\times} = [90, 180, 270]$ deg, which equal to stand-on, head-on, give-way encounters, for the dynamic scenarios are presented. The agent's decision-making in terms of the conducted manoeuvring in the static and dynamic scenarios are presented in Figure 6.35 and in Figure 6.36, respectively.

In the static scenarios it can be derived that the return that the agent accumulates is 513.23 when $e_{XT,obs} = 87.5$ m, 498.39 when $e_{XT,obs} = 0$ m, and 505.62 when $e_{XT,obs} = -87.5$ m, which suggest that the agent conducts a bigger evasive manoeuvre in the more critical scenario where the obstacle is allocated central to the path. Also, the agent conducts an efficient manoeuvre by conducting a starboard-side evasive manoeuvre when $e_{XT,obs} = 87.5$ m and port-side evasive manoeuvre when

$e_{\text{XT,obs}} = -87.5$ m. The difference of the accumulated returns when $e_{\text{XT,obs}} = -87.5$ m and $e_{\text{XT,obs}} = 87.5$ m can be attributed to the port-side manoeuvre noted when $e_{\text{XT,obs}} = 0$ m, which suggests that the agent decision-making has potentially more bias towards port-side manoeuvre in the static scenario.

In the dynamic scenarios the agent accumulates 478.20 when $\Theta_{\times} = 90$ deg, 420.46 when $\Theta_{\times} = 180$ deg, and 352.38 when $\Theta_{\times} = 270$ deg, which suggest that the agent conducts bigger evasive manoeuvre in the give-way encounter, followed by the head-on and stand-on encounters. The bigger evasive manoeuvre during the give-way encounter can be attributed to the earlier minimum obstacle detection, as indicated by the timestep *, which is due to the slower nominal speed of the obstacle compared to the OS. It is also worth noting that in the stand-on scenario the OS still conducts an evasive manoeuvre due to the obstacle violating the COLREG by maintaining its speed and orientation. Thus, it is derived that the agent decision-making is capable of conducting different evasive manoeuvres by prioritising efficiency in the static scenarios and prioritising COLREG compliance in the dynamic scenarios. The actor's policy in terms of the commanded rudder angle δ_C per timestep t is presented in Figure 6.37.

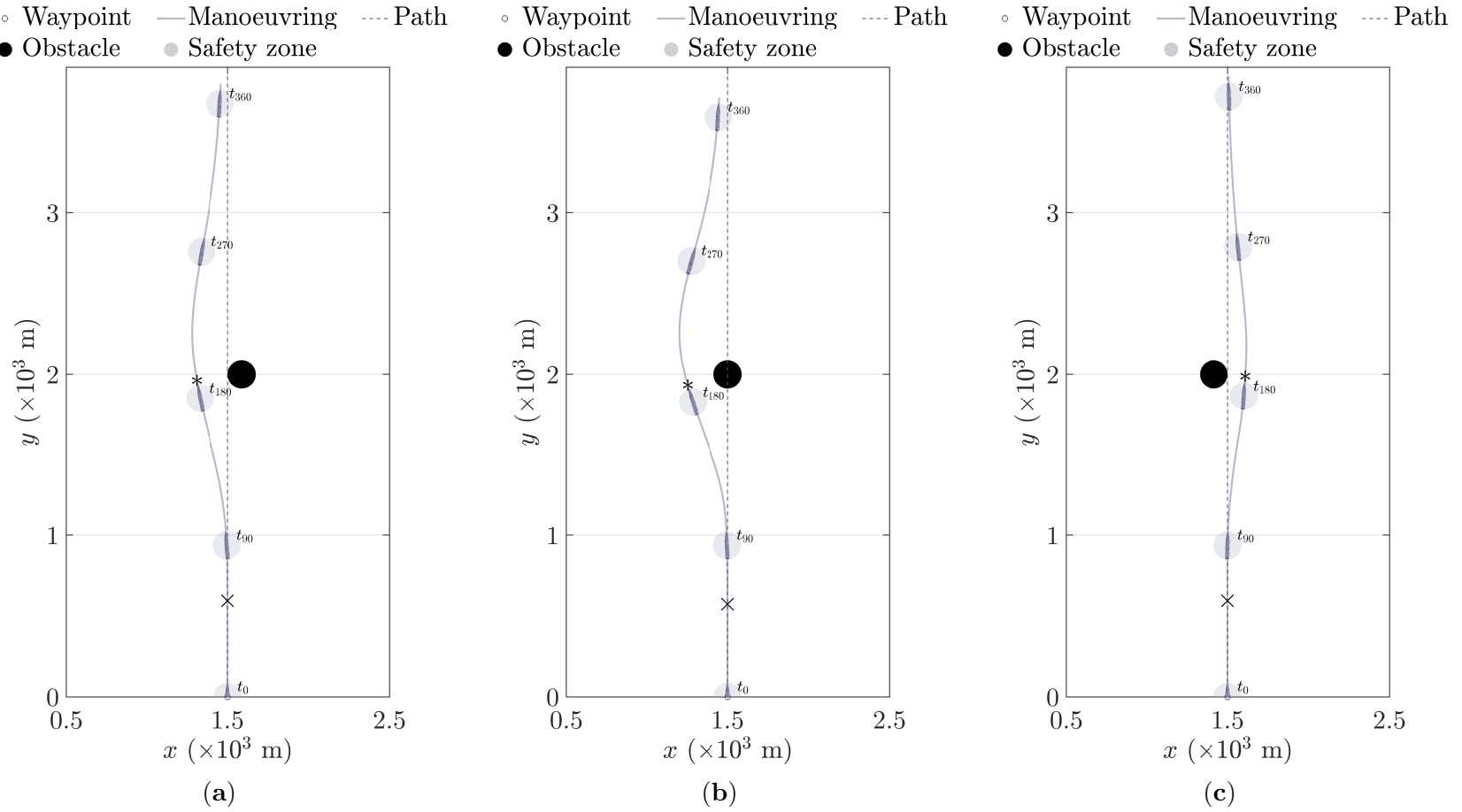


Figure 6.35 Decision-making of the agent in terms of the conducted manoeuvring in the static scenarios when (a) $e_{XT,obs} = -87.5$ m, (b) $e_{XT,obs} = 0$ m, and (c) $e_{XT,obs} = 87.5$ m. The position of the OS is plotted every 90 s. The $\times$ and $*$ represent the timesteps of the first and minimum obstacle detection, respectively.

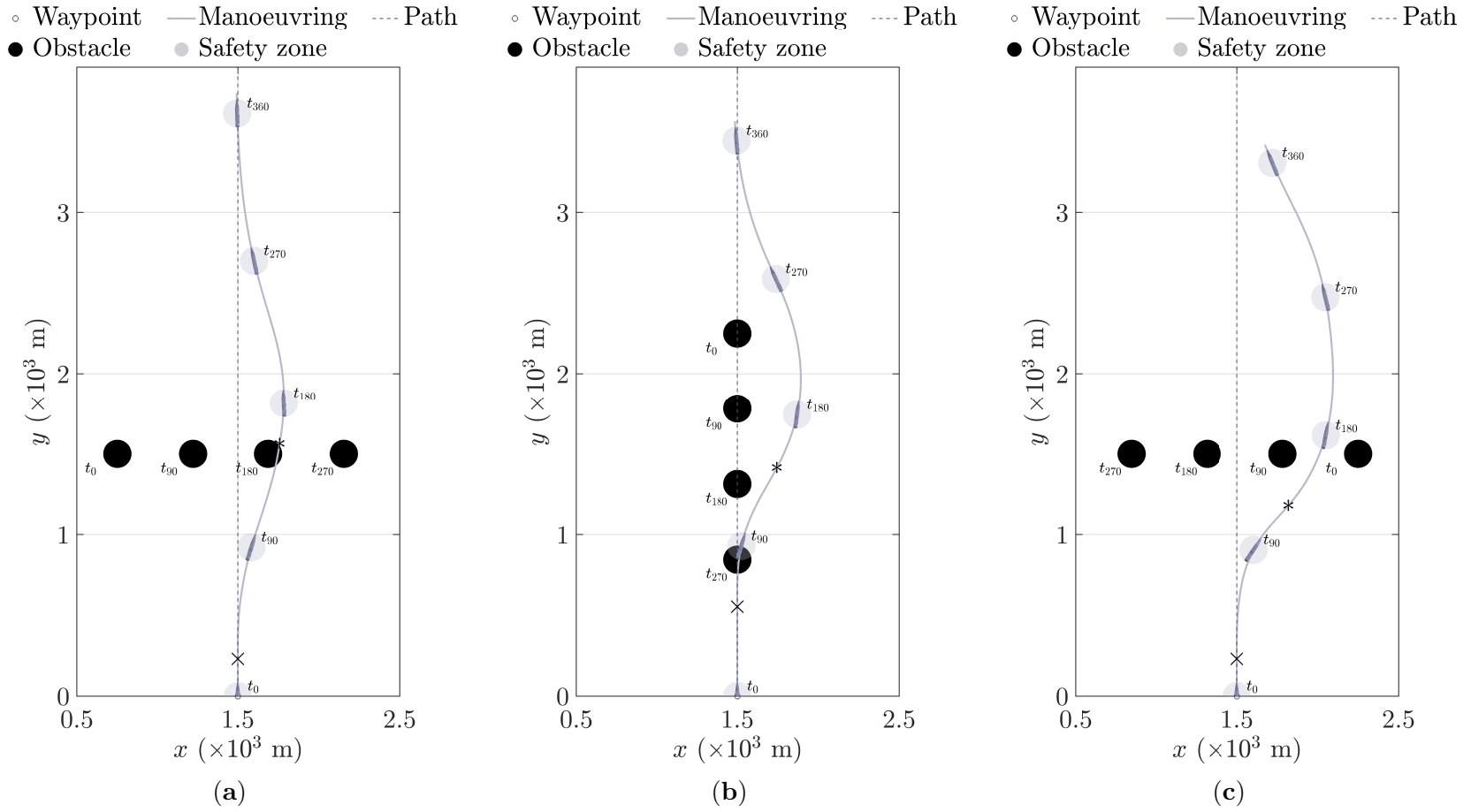


Figure 6.36 Decision-making of the agent in terms of the conducted manoeuvring in the dynamic scenarios when (a) $\Theta_x = 90$ deg, (b) $\Theta_x = 180$ deg, and (c) $\Theta_x = 270$ deg. The position of the OS is plotted every 90 s. The $\times$ and $*$ represent the timesteps of the first and minimum obstacle detection, respectively.

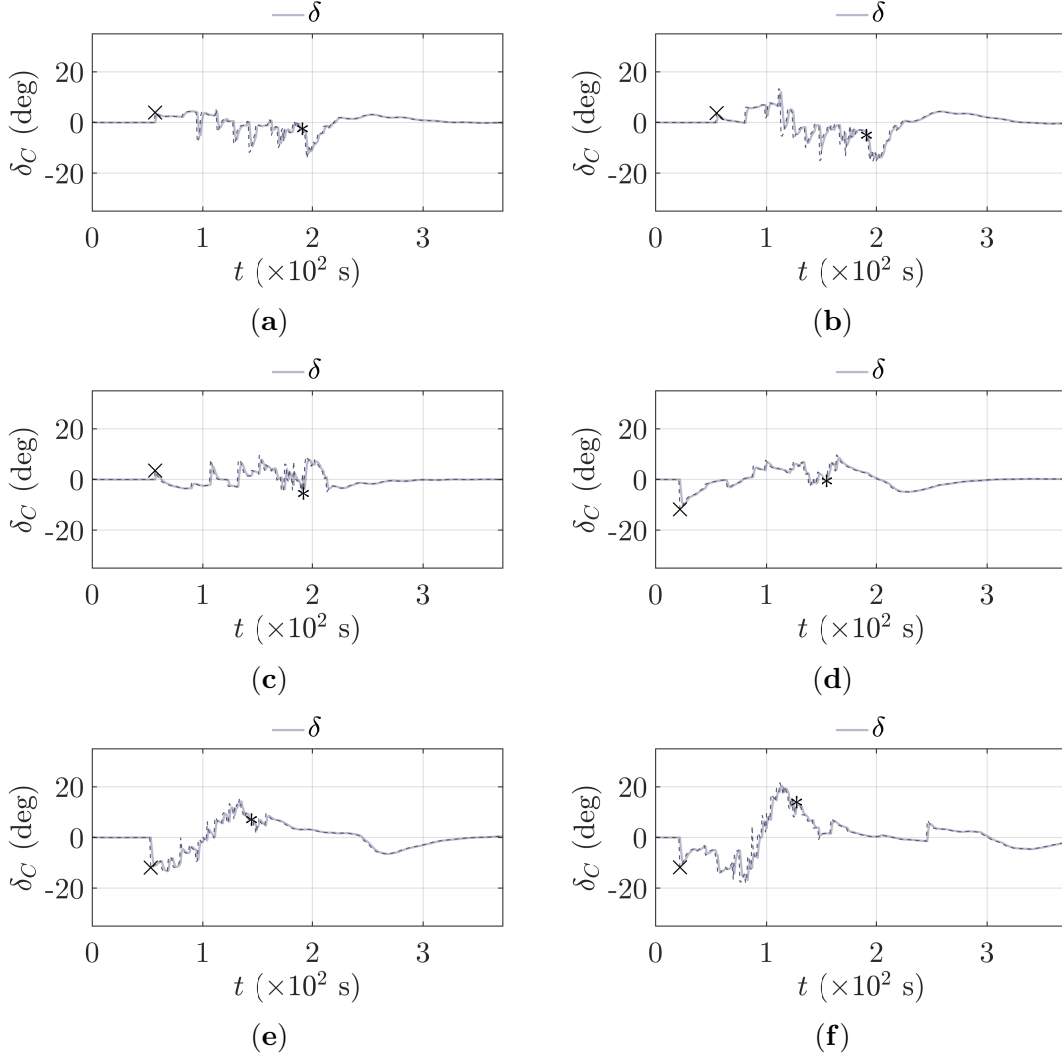


Figure 6.37 Actor’s policy of the agent in terms of the commanded rudder angle δ_C per timestep t in the static scenarios when (a) $e_{XT,obs} = -87.5$ m, (b) $e_{XT,obs} = 0$ m, and (c) $e_{XT,obs} = 87.5$ m and in the dynamic scenarios when (d) $\Theta_x = 90$ deg, (e) $\Theta_x = 180$ deg, and (f) $\Theta_x = 270$ deg. The $\times$ and $*$ represent the timesteps of the first and minimum obstacle detection, respectively.

The robustness of the agent’s decision-making against unclassified static obstacles in terms of the robustness metric for collision avoidance efficiency $RM_{CAE,*}$, is presented in Table 6.22 and Figure 6.38. Specifically, the robustness metrics are measured within the trained position envelope. It is noted that the robustness threshold for collision avoidance efficiency is violated between $e_{XT,obs} = 5\text{--}40$ m, which verify the prior noted bias of the agent towards starboard-side evasive manoeuvre. However, it is worth noting that in all scenarios the agent conducts successful evasive manoeuvres without leading to a collision. In addition, a generally stable robustness metric throughout the whole scenarios indicates good generalisation capabilities of keeping the same safety distance across different obstacle positions. Finally, it is

speculated that the robustness can be further increased upon longer training time and termination of training at an appropriate stage.

Table 6.22 Robustness of the agent’s decision-making against unclassified static obstacles in terms of the robustness metric for collision avoidance efficiency $RM_{CAE,*}$.

$e_{XT,obs}$ (m)	$RM_{CAE,*}$ (m)
-87.5	194.37
-52.5	185.48
-17.5	176.43
17.5	-160.52
52.5	105.29
87.5	108.66

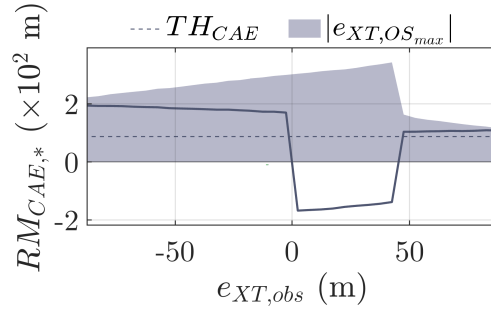


Figure 6.38 Robustness of the agent’s decision-making against unclassified static obstacles in terms of the robustness metric for collision avoidance efficiency $RM_{CAE,*}$.

The robustness of the agent’s decision-making against unclassified dynamic obstacles in terms of the robustness metric for COLREG compliance $RM_{CC,*}$, is presented in Table 6.23 and Figure 6.39. Specifically, the robustness metrics are measured within the trained orientation envelope. It is noted that the robustness threshold for COLREG compliance is compliant throughout the whole envelope, even during stand-on encounters where the obstacle violates the COLREG by maintaining the speed and orientation.

Table 6.23 Robustness of the agent’s decision-making against unclassified dynamic obstacles in terms of the robustness metric for COLREG compliance $RM_{CC,*}$.

Θ_x (deg)	$RM_{CC,*}$ (m)
90	304.73
135	231.18
180	171.47
225	122.44
270	123.37

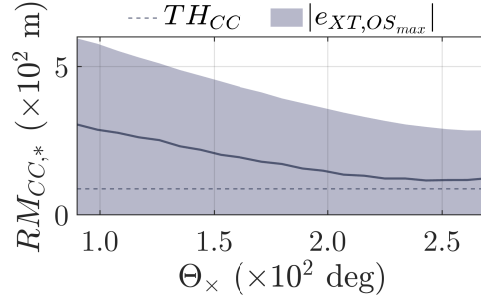


Figure 6.39 Robustness of the agent's decision-making against unclassified dynamic obstacles in terms of the robustness metric for COLREG compliance $RM_{CC,*}$.

6.5.3 DL-Based Agent Training & Decision-Making Agent's Robustness Verification

The robustness of the agent's decision-making against unclassified obstacles scenarios outside of the trained envelope are investigated. Specifically, the same scenarios are simulated without using the ideal scenario identification observation but using a classification agent that learns to classify a static, dynamic, or obstacle-free scenario as -1 , 1 , and 0 , respectively. The training of the classification agent is presented in Figure 6.40. Specifically, 70% of the accumulated data are used for training of the scenario classification agent, which is trained for 1,000 iterations. At the end of training the loss is decreased at 7.5×10^{-3} with an accuracy of 98.96% using 30% of the accumulated data.

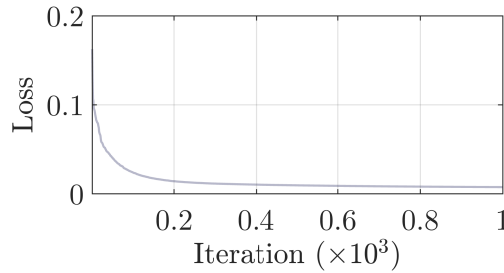


Figure 6.40 Loss per iteration during the training of the classification agent.

The robustness of the agent's decision-making against unclassified static obstacles using a scenario classification agent in terms of the robustness metric for collision avoidance efficiency $RM_{CAE,*}$, is presented in Table 6.41 and Figure 6.24. It is noted that the $RM_{CAE,*}$ follows a similar trend as when not using the scenario classification agent. Maximum reduction of 4.78% is noted when $e_{XT,obs} = -32.5$ m,

where the $RM_{CAE,*}$ m is decreased from 180.43 m to 171.81 m. This is in alignment with the classification accuracy that exhibits the lowest accuracy of 98.12% when $e_{XT,obs} = -32.5$ m. The reduction of $RM_{CAE,*}$ using a classification agent can be attributed to the 1.88% of inaccurate scenario classification leading to delayed evasive manoeuvres. It is worth noting that $RM_{CAE,*}$ where the threshold is violated is not considered, for instance, when $e_{XT,obs} = 42.5$ m, where the $RM_{CAE,*}$ is increased by 174.78% due to the bias towards port-side evasive manoeuvre.

Table 6.24 Robustness of the agent’s decision-making against unclassified static obstacles using a scenario classification agent in terms of the robustness metric for collision avoidance efficiency $RM_{CAE,*}$.

$e_{XT,obs}$ (m)	$RM_{CAE,*}$ (m)	$e_{XT,obs}$ (m)	Classification accuracy	$RM_{CAE,*}$ (m)
-87.5	194.37	-87.5	98.93%	191.92
-52.5	185.48	-52.5	98.39%	180.63
-17.5	176.43	-17.5	98.12%	168.57
17.5	-160.52	17.5	98.66%	-150.83
52.5	105.29	52.5	99.73%	104.02
87.5	108.66	87.5	99.46%	108.86

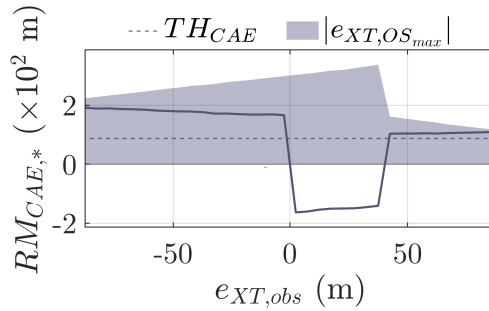


Figure 6.41 Robustness of the agent’s decision-making against unclassified static obstacles using a scenario classification agent in terms of the robustness metric for collision avoidance efficiency $RM_{CAE,*}$.

The robustness of the agent’s decision-making against unclassified dynamic obstacles using a scenario classification agent in terms of the robustness metric for COLREG compliance $RM_{CC,*}$, is presented in Table 6.42 and Figure 6.25. It is noted that the $RM_{CC,*}$ follows a similar trend as when not using the scenario classification agent. Maximum reduction of 4.02% is noted when $\Theta_x = 270$ deg, where the $RM_{CC,*}$ m is decreased from 123.37 m to 118.41 m. This is in alignment with the classification accuracy that exhibits the lowest accuracy of 97.59% when $\Theta_x = 270$ deg. The reduction of $RM_{CC,*}$ using a classification agent can be attributed to the 2.41% of inaccurate scenario classification leading to delayed evasive manoeuvres. From both

$RM_{CAE,*}$ and $RM_{CC,*}$ is noted that the classification accuracy has direct impact on the robustness metrics.

Table 6.25 Robustness of the agent’s decision-making against unclassified static obstacles using a scenario classification agent in terms of the robustness metric for COLREG compliance $RM_{CC,*}$.

$\Theta_{\times}$ (deg)	$RM_{CC,*}$ (m)	$\Theta_{\times}$ (deg)	Classification accuracy	$RM_{CC,*}$ (m)
90	304.73	90	100%	304.73
135	231.18	135	100%	231.18
180	171.47	180	99.73%	171.47
225	122.44	225	98.66%	122.43
270	123.37	270	97.59%	118.41

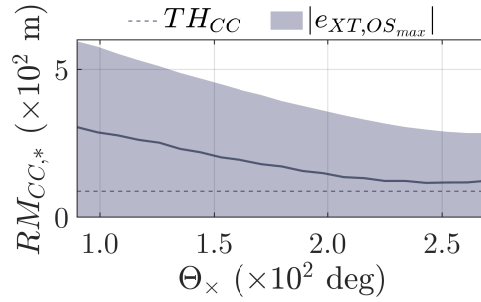


Figure 6.42 Robustness of the agent’s decision-making against unclassified static obstacles using a scenario classification agent in terms of the robustness metric for COLREG compliance $RM_{CC,*}$.

The robustness of the agent’s decision-making against unclassified obstacles scenarios outside of the trained envelope is investigated. Specifically, the same scenarios are simulated using different obstacle shapes, but for brevity, only the results pertaining to an obstacle size $L_{\text{obs}} = 12$ m and $B_{\text{obs}} = 5$ m for the dynamic scenario are presented. The agent’s decision-making in terms of the conducted manoeuvring in the dynamic scenarios is presented in Figure 6.43. It is noted that in all scenarios the encounters lead to a collision due to the violation of the collision criteria.

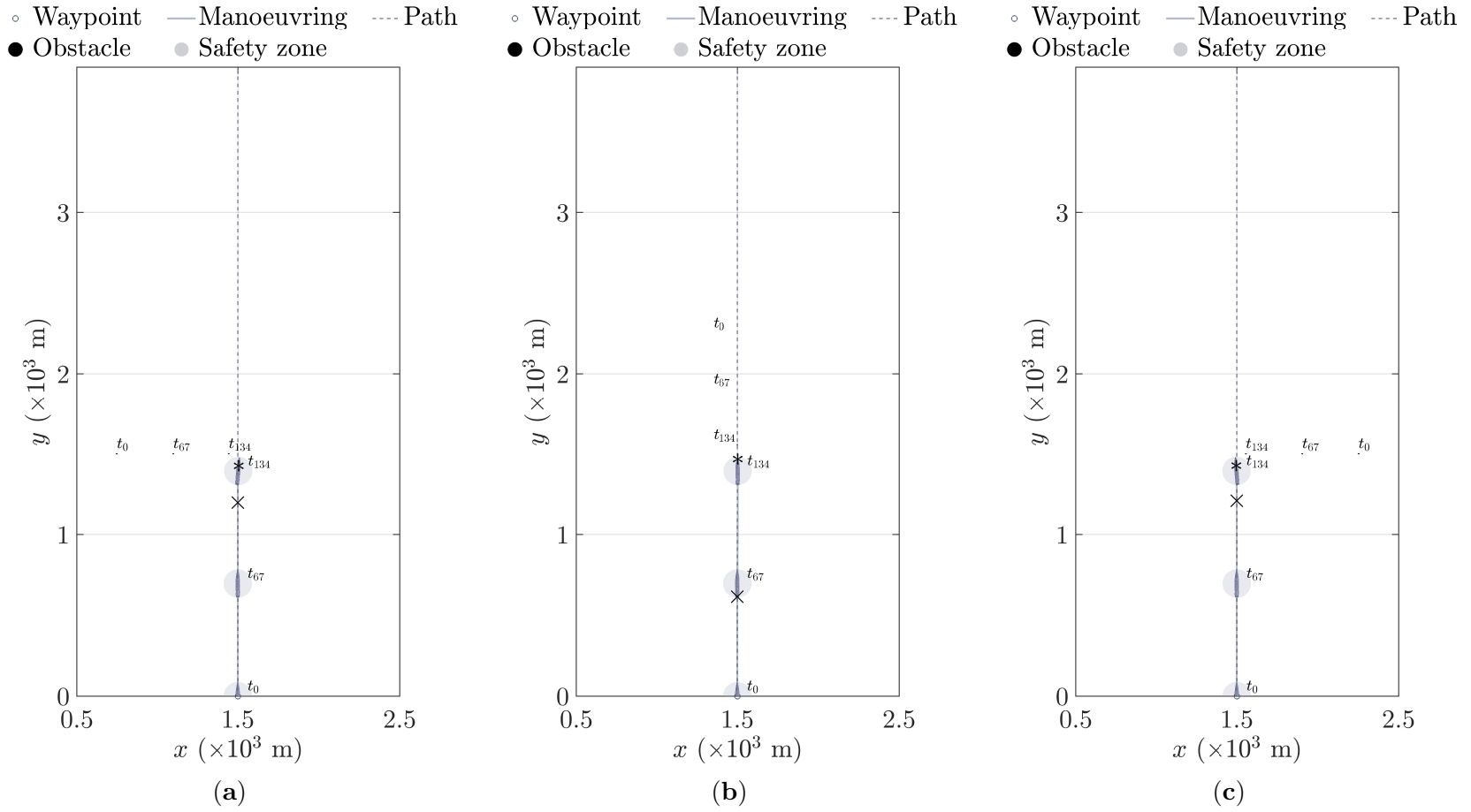


Figure 6.43 Decision-making of the agent_B in terms of the conducted manoeuvring when (a) $\sigma^2 = 0$ m² and (b) $\sigma^2 = 25$ m². The position of the OS is plotted every 70 s. The $\times$ and $*$ represent the timesteps of the first and minimum obstacle detection, respectively.

The robustness of the agent's decision-making against unclassified dynamic obstacles of $L_{\text{obs}} = 12$ m and $B_{\text{obs}} = 5$ m using a scenario classification agent in terms of the robustness metric for COLREG compliance $RM_{CC,*}$, is presented in Table 6.26 and Figure 6.44. It is noted that the threshold is violated in all scenarios, despite the minimum classification accuracy exhibiting 98.56%. Considering that maximum $|e_{\text{XT},\text{OS}_{\text{max}}}|$ noted is only 7.30 m, suggests that in all scenarios the agent conducts straight-path following due to the inability of 41 LIDAR measurements to detect the small obstacle.

Table 6.26 Robustness of the agent's decision-making against unclassified dynamic obstacles of $L_{\text{obs}} = 12$ m and $B_{\text{obs}} = 5$ m using a scenario classification agent in terms of the robustness metric for COLREG compliance $RM_{CC,*}$.

$\Theta_{\times}$ (deg)	Classification accuracy	$RM_{CC,*}$ (m)
90	100%	-82.21
135	100%	-75.52
180	99.30%	48.43
225	100%	71.90
270	100%	85.81

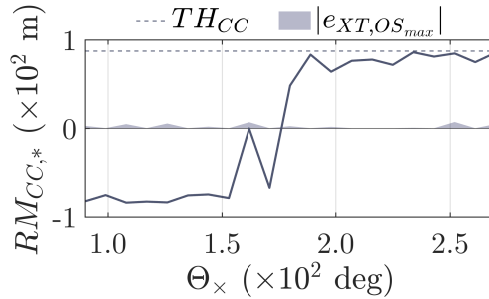


Figure 6.44 Robustness of the agent's decision-making against unclassified dynamic obstacles of $L_{\text{obs}} = 12$ m and $B_{\text{obs}} = 5$ m using a scenario classification agent in terms of the robustness metric for COLREG compliance $RM_{CC,*}$.

To resolve this issue, the LIDAR measurements are increased from 41 to 401, while maintaining the same decision-making and classification agents. Specifically, the minimum obstacle detection of every 10th LIDAR measurements is used as input to the agents. The agent's decision-making in terms of the conducted manoeuvring in the dynamic scenarios using more LIDAR measurements is presented in Figure 6.45. It is noted that in all scenarios the collision criteria is not violated.

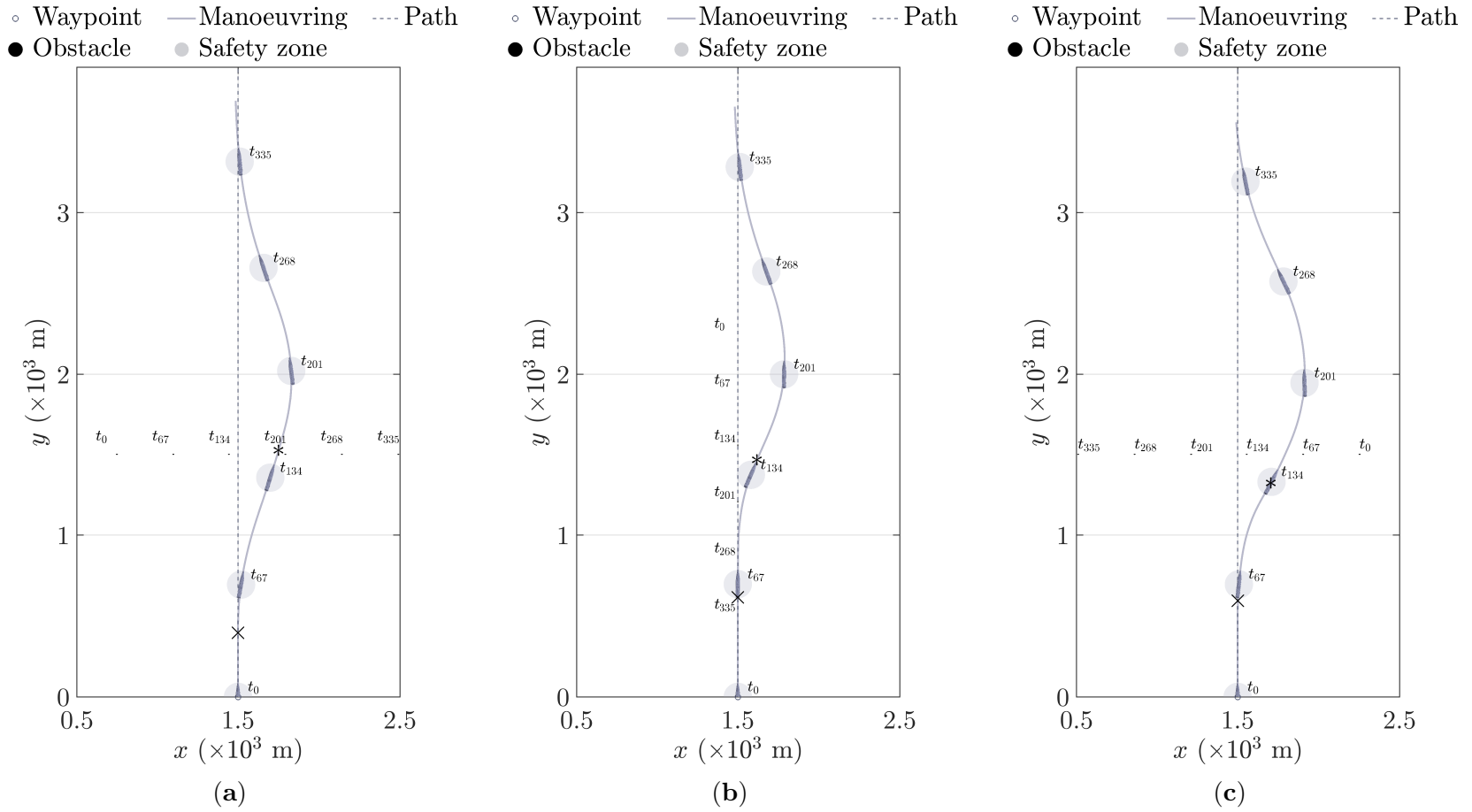


Figure 6.45 Decision-making of the agent_B in terms of the conducted manoeuvring when (a) $\sigma^2 = 0$ m² and (b) $\sigma^2 = 25$ m². The position of the OS is plotted every 70 s. The $\times$ and $*$ represent the timesteps of the first and minimum obstacle detection, respectively.

The robustness of the agent's decision-making against unclassified dynamic obstacles of $L_{\text{obs}} = 12$ m and $B_{\text{obs}} = 5$ m using a scenario classification agent and 401 LIDAR measurements in terms of the robustness metric for COLREG compliance $RM_{CC,*}$, is presented in Table 6.27 and Figure 6.46. It is noted that the threshold is no longer violated, except when $\Theta_{\times} = 10 - 12$ deg, but is speculated that further increase of the robustness can be achieved upon increasing the number of LIDAR measurements. This lends credence to the agent's decision-making capability to robustly conduct different evasive manoeuvres according to real-time classification of the encountered obstacles without prior knowledge, which is particularly important when encountering small vessels below 300 gross tonnage that are not required to be equipped with AIS [274].

Table 6.27 Robustness of the agent's decision-making against unclassified dynamic obstacles of $L_{\text{obs}} = 12$ m and $B_{\text{obs}} = 5$ m using a scenario classification agent and 401 LIDAR measurements in terms of the robustness metric for COLREG compliance $RM_{CC,*}$.

$\Theta_{\times}$ (deg)	Classification accuracy	$RM_{CC,*}$ (m)	$\Theta_{\times}$ (deg)	Classification accuracy	$RM_{CC,*}$ (m)
90	100%	-82.21	90	94.10%	228.73
135	100%	-75.52	135	97.86%	236.43
180	99.30%	48.43	180	99.46%	123.26
225	100%	71.90	225	99.46%	173.15
270	100%	85.81	270	100%	213.59

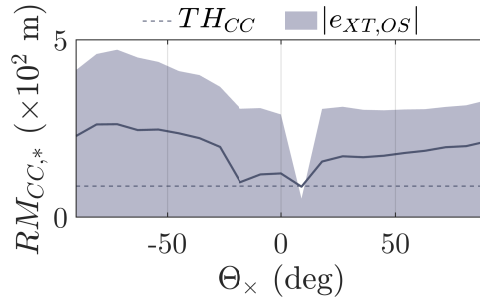


Figure 6.46 Robustness of the agent's decision-making against unclassified dynamic obstacles of $L_{\text{obs}} = 12$ m and $B_{\text{obs}} = 5$ m using a scenario classification agent and 401 LIDAR measurements in terms of the robustness metric for COLREG compliance $RM_{CC,*}$.

6.5.4 Decision-Making Agent's Robustness Validation

A preliminary experimental setup is investigated for a small-scale validation of this approach. Specifically, the experimental setup considers a 2 m catamaran vessel

that autonomously conducts COLREG-compliant evasive manoeuvres during the encounter with a dynamic obstacle. The catamaran vessel is equipped with a LIDAR sensor, Ouster OS1, that is used to acquire distance and angular measurements. The effectiveness of this approach is presented in Figure 6.47.



Figure 6.47 Timesteps of the experimental validation during (a) the initial position prior to detecting the obstacle, (b) the COLREG-compliant evasive manoeuvre, and (c) arrival to the final destination after path recovery.

Chapter 7

Final Remarks & Future Work

7.1 Case Studies Findings

The main findings from the case studies are as follows.

1. The developed FT diagram provided a robust representation of the failure of the CAS with reasonable MTBF data that enabled the accurate identification of the most critical components, failure mechanisms, and recommendation of cost-effective risk-reducing measures without the need of sensitivity analysis during its early design phase.
2. The CAS operating in adverse weather and daylight illumination condition (mode 3) exhibited the highest probability of failure, reaching up to 32% when operated for 730 h. The most critical components and failure mechanisms were related to the ICS and SAS, mainly the echo sounder, current profiler, visibility & weather sensor, anemometer, microphone, LCD panels, navigational lights, and speaker.
3. Identical or functional redundancy as a risk-reducing measure to the relatively inexpensive but critical components of the ICS and SAS was found to be effective in reducing the probability of failure of the CAS operating in mode 3 up to 91%.
4. The propulsion & steering system was found to be the most critical component in the risk-informed CAS reconfiguration, therefore indicating the need of intelligent monitoring and health assessment systems and/or alternative power plants as an effective risk-reducing measure.
5. The trained DDPG agent exhibited enhanced sophisticated and robust decision-

making by conducting different evasive manoeuvres when the dynamic safety domain was bigger. Robustness was verified even when the safety domain was increased 18.9% from its maximum trained value and the importance of this behaviour considering the modelling of the dynamic safety domain as a function of the probability of failure of the CAS was discussed.

6. The trained DDPG agent exhibited enhanced sophisticated and robust decision-making beyond the pre-settled control strategies during the propeller-rudder coupled control. Specifically, the sophisticated control of the DDPG agent by increasing the propeller revolution during the evasive manoeuvre as a compensating mechanism against the speed loss and to achieve sharper evasive manoeuvre was noted. Robustness was verified even when the obstacle size was increased 210% from its trained value.
7. The trained DDPG agent exhibited enhanced sophisticated decision-making prioritising safety over efficiency when the noise variance was higher. Specifically, the decision-making of the DDPG agent over the rewards exploited less the path following, nominal navigation, and actuator control rewards over the collision avoidance reward, manifested as larger evasive manoeuvres.
8. The actor's policy exhibited enhanced expressiveness by outputting different commanded rudder angles depending on the noise variance. Specifically, major difference in the commanded rudder angles was evident during the evasive manoeuvre verifying the DDPG agent's sophisticated decision-making. Also, the actor initiated an evasive manoeuvre by successfully discerning genuine obstacle detections amidst noisy measurements, which was attributed to the great feature extraction capabilities of DNNs.
9. The critic's estimation exhibited enhanced adaptability by adjusting its optimism and conservatism depending on the noise variance. Specifically, the critic learned to underestimate the expected return when the noise variance was higher verifying the actor's policy expressiveness. The critic's conservatism was attributed to the higher probability of triggering the collision criterion in higher noise variances.
10. Sensitivity analysis indicated the criticality of the noise variance observation for the DDPG agent's decision-making. Specifically, major differences in the actor's

and critic's outputs were noted during the variations of the noise variance observation and not during the variations of the LIDAR measurements observation. However, the LIDAR measurements observation was found to be responsible for the erratic output.

11. The robustness of the DDPG agent's decision-making against noise variance was verified up to 132% from its maximum trained value. Specifically, the robustness for path following decreased with the increase of noise variance, but the robustness for collision avoidance increased by 52.6% from its initial value considering minimum noise variance. The increase of robustness was attributed to the DDPG agent's ability to generalise its sophisticated decision-making across higher noise variances.
12. The robustness of the DDPG agent's decision-making against noise variance was verified only up to 76% from its maximum trained value, when trained without the noise variance observation. Specifically, the robustness for collision avoidance exhibited a decreasing trend with the increase of noise variances. This was attributed to the far less sophisticated decision-making, lack of expressiveness of the actor's policy and adaptability of the critic's estimation, with worse generalisation capabilities, highlighting the effectiveness of the proposed methodology.
13. The trained DDPG agent exhibited robust decision-making against unclassified obstacles. Specifically, the DDPG agent conducted efficient evasive manoeuvres when encountering static obstacles and COLREG-compliant evasive manoeuvres when encountering dynamic obstacles. The DDPG agent's compliance with COLREG was found even when the dynamic obstacle violated the rules during a stand-on encounter by maintaining its heading and velocity.
14. The trained FNN agent exhibited accurate classification against unclassified obstacles in real-time even when prior information about the classification of the encountered obstacles was not known apriori. Specifically, the FNN agent was capable of classifying the detected obstacle with accuracy above 98.12%.
15. The trained DDPG agent exhibited robust decision-making even when the obstacle size was decreased by 88.5% by increasing the LIDAR detection measurements

from 41 to 401. The effectiveness of this approach particularly during the encounter with small vessels that are not obliged to be fitted with AIS data was discussed.

7.2 Achievement of Aims & Objectives

The effectiveness of this research in addressing the aim of this research is evaluated in an inductive manner. Specifically, the aim of this research was decomposed into high-level research objectives after the elaboration of the problem statement and these objectives in return were decomposed into more specific low-level research objectives after the identification of research gaps from the pertinent literature.

Table 7.1 Case studies with their correlated low-level research objectives and phases.

Case study finding	Low-level research objectives	High-level research objectives
1	1	1
2	1	1
3	1	1, 2
4	1	1
5	2, 5, 7, 8	2, 3, 4
6	5, 6, 7, 8	2, 3, 4
7	3, 5, 7, 8	2, 3, 4
8	3, 7, 8	3
9	3, 7, 8	3
10	3	3
11	3, 5, 8	2, 3, 4
12	3, 7, 8	2, 3, 4
13	4, 5, 8	2, 3, 4
14	4	3
15	4, 5, 8	2, 3, 4

7.3 Novelty & Implications

The novelty of this research stems from the proposal of a research methodology that enhances the robustness of decision-making for the reactive collision avoidance of

MASSs under critical collision scenarios. The key novelty aspects are outlined below.

1. Risk-informed design of the CAS for next-generation MASSs that is compliant with current IMO instruments.
2. Proposal of different CAS configurations based on different weather and illumination conditions.
3. Identification of critical internal risk metrics pertaining to the CAS, including critical components and failure modes.
4. Evaluation of the effectiveness and limitation of risk-reducing measures from cost-benefit perspective.
5. Integration of internal risk metrics into CRIs for a holistic assessment of the collision risk.
6. Investigation of critical reactive collision scenarios with a limited detecting range compared to the manoeuvrability of the investigated vessel.
7. Investigation of critical collision scenarios considering dynamic safety domain, perception sensor noise, and unclassified obstacles.
8. Consideration of a propeller-rudder coupled control approach.
9. Formulation of the decision-making problem and development of training frameworks to enhance the robustness of DRL-based agents against critical CRIs.
10. Identification of particular CRIs that DRL-based agents are the most sensitive and prone to impacting the decision-making output.
11. Real-time obstacle classification using DL-based agent without prior information.

The implications of this research expand in further investigation in the academia and practical application in the industry, which include but are not limited to:

1. Supporting the decision-making pertaining to the design of CAS for the next-generation MASSs that are compliant with regulations and risk-informed.
2. Enhance the survivability of MASSs against unknown-unknown events through the enhancement of robust decision-making pertaining to their reactive collision avoidance.

3. Development of AI systems, whose decision-making can be explained and whose sensitivity can be assessed, with further implications in human-in-the-loop autonomous systems.

7.4 Future Work

The limitations of this research include the currently non-existent regulatory instruments specific to MASSs, the uncertainty of the acquired failure data, especially of the AI software, and the lack of acceptable safety thresholds for safety-critical systems of MASSs. Other limitations include the assumption of ideal environmental conditions with no disturbances and the use of generic noise model that is not specific to the pertinent condition. Another significant limitation is the heavy computation effort required for the training of DRL-based agents and their great sensitivity to hyperparameter settings. Finally, the difficulty of analytically interpreting the decision-making of DRL-based agents as black-boxes and the lack of large-scale validations in experimental setup are major limitations to this research.

Future work includes the consideration of additional components to the CAS, including cyber-security systems and the investigation of specific accident scenarios. In addition, the development of more realistic digital twins and scenarios of higher fidelity, including environmental disturbances, system health condition, etc, will be addressed. More challenging scenarios of multiple static and dynamic obstacles need to be investigated. How to robustly conduct reactive collision avoidance amidst multiple static and dynamic obstacles without prior information of their classification is a challenge to be addressed in future work. Efforts to further investigate the training of AI-based agents that extend beyond the hyperparameters optimisation and effectively affect the training performance, such as selection of mini-batch, need to be investigated.

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Appendix A

Deep Deterministic Policy Gradient Algorithm Pseudo-code

Algorithm 1: Deep deterministic policy gradient

Initialise $Q(s, a \mid \theta^Q)$ with random θ^Q and $Q'(s, a \mid \theta^{Q'})$ with $\theta^{Q'} \leftarrow \theta^Q$;

Initialise $\mu(s \mid \theta^\mu)$ with random θ^μ and $\mu'(s \mid \theta^{\mu'})$ with $\theta^{\mu'} \leftarrow \theta^\mu$;

Initialize $\mathcal{D}$;

for $\text{Episode} = 1, \dots$ **do**

 Initialize $\mathcal{W}$;

 Receive s_1 ;

for $t = 1, \mathcal{T}$ **do**

 Set $a_t = \mu(s_t \mid \theta^\mu) + \mathcal{W}_t$;

 Execute a_t , receive r_t and s_{t+1} ;

 Store (s_t, a_t, r_t, s_{t+1}) in $\mathcal{D}$;

 Sample $\mathcal{B}$ of (s_i, a_i, r_i, s_{i+1}) , $i = 1, \dots, b$ from $\mathcal{D}$;

 Set $y_i = r_i + \gamma Q'(s_{i+1}, \mu'(s_{i+1} \mid \theta^{\mu'}) \mid \theta^{Q'})$;

 Calculate $\nabla_{\theta^Q} L = \frac{1}{b} \sum_{i=1}^b \nabla_{\theta^Q} (y_i - Q(s_i, a_i \mid \theta^Q))^2$;

 Calculate $\nabla_{\theta^\mu} J = \frac{1}{b} \sum_{i=1}^b \nabla_a Q(s_i, a \mid \theta^Q) \big|_{a=\mu(s_i \mid \theta^\mu)} \nabla_{\theta^\mu} \mu(s_i \mid \theta^\mu)$;

 Update $\theta^Q \leftarrow \theta^Q - a_Q \nabla_{\theta^Q} L$;

 Update $\theta^\mu \leftarrow \theta^\mu + a_\mu \nabla_{\theta^\mu} J$;

 Update $\theta^{Q'} \leftarrow \tau \theta^Q + (1 - \tau) \theta^{Q'}$;

 Update $\theta^{\mu'} \leftarrow \tau \theta^\mu + (1 - \tau) \theta^{\mu'}$;

end

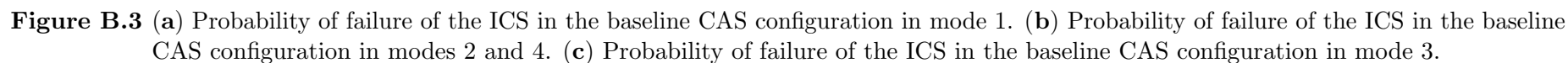
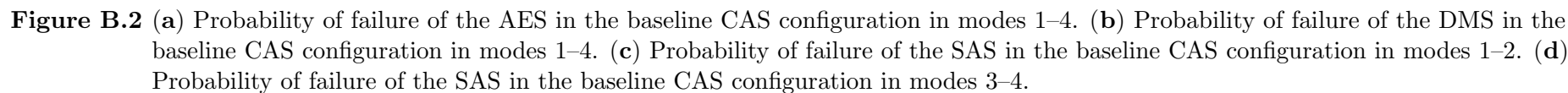
end

Appendix B

Fault Tree Analysis Results



Figure B.1 (a) Probability of failure of the baseline CAS configuration in mode 1. (b) Probability of failure of the baseline CAS configuration in mode 2. (c) Probability of failure of the baseline CAS configuration in mode 3. (d) Probability of failure of the baseline CAS configuration in mode 4.





(c)