Probabilistic Risk Analysis for Ship Collision-Theory and Application for Conventional and Autonomous Ships

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Probabilistic Risk Analysis for Ship Collision

-Theory and Application for Conventional and Autonomous Ships

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Delft University of Technology

Probabilistic Risk Analysis for Ship Collision

-Theory and Application for Conventional and Autonomous Ships

Proefschrift

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Dedicated to
Sihui Hu, Jinrong Zhu, and Xuanyi Chen

Preface

The whole experience of PhD life of mine is like a dream. Walking down the memory lane now, I can still recall the feeling on my first day in TU Delft vividly: proud, curious, and overwhelmed. During these years, many things happened, and many people came into my work and life, which helped me to walk firmly on the bright path towards the future. With this opportunity, I would like to express my sincere gratitude to all the people that I have met during my PhD life.

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List of Symbols

ConfP	Conflict Position
$P_{Collision}$	Collision probability
$P_{Geometric}$	Geometric probability of collision
$P_{Causation}$	Causation probability of collision
D_{ij}	Collision diameter
D_{cpa}	Distance to CPA
N_a	Number of collision candidates
$VO_{A\|B}$	Velocity obstacle sets of ship A induced by B
R	Radius of ConfP
T_{cpa}	Time to CPA
$P(t_C)$	Position of ship at collision time t_C
t_C	Time of collision
L	Length of ship
$P(t)$	Position of ship at time t
t	Time
$V(t)$	The velocity of ship at time t
t_0	Time horizon
$T_{linking}$	Linking threshold
T_{Scan}	Scanning interval
$p(X)$	Probability of variable X
$K(X_i\|\pi_i)$	Credal set given evidence π_i
π_i	Evidence
Ω_x	Sample space

List of Acronyms and Abbreviations

AI	Artificial Intelligence
AGV	Autonomous Guided Vessel
AIS	Automatic Information System
ARPA	Automatic Radar Plotting Aid
BN	Bayesian Network
CD	Collision Diameter
CN	Credal Network
COLREGs	Convention on the International Regulations for Preventing Collisions at Sea, 1972
CPA	Closest Point of Approach
CPT	Conditional Probability Table
CTPA	Collision Threat Parameter Area
DCPA	Distance to Closest Point of Approach
DDV	The degree to Domain Violation
EMSA	European Maritime Safety Administration
ET	Event Tree
FQSD	Fuzzy Quaternion Ship Domain
FSA	Formal Safety Assessment
FTA	Fault Tree Analysis
GISIS	Global Integrated Shipping Information System
GRACAT	GRounding And Collision Analysis Toolbox
HFACS	Human Factors and Classification System
HOF	Human and Organizational Factors
HRA	Human Reliability Analysis
IALA	International Association of Marine Aids to Navigation and Lighthouse Authorities
IDAC	Information process-Decision making-Action execution of Crew
IMO	International Maritime Organisation

IWRAP	International Association of Lighthouse Authorities Waterways Risk Assessment Program
KPI	Key Performance Indicators
Lidar	Light Detection And Ranging
LVO	Linear Velocity Obstacle
MASS	Maritime Autonomous Surface Ship
MDTC	Minimum Distance To Collision
MMSI	Maritime Mobile Service Identifier
MPR	Market Penetration Ratio
MPC	Model Predictive Control
MSA	Maritime Safety Administration
MUNIN	Maritime Unmanned Navigation through Intelligence in Networks
NLVO	Non-Linear Velocity Obstacle
NTCT	Navigational Traffic Conflict Technique
OOW	Officers on Watch
ORCAS	Online risk management and Risk Control for Autonomous Ships
PRA	Probabilistic Risk Analysis
RCC	Remote Control Centre
SAMSON	Safety Assessment Model for Shipping and Offshore on the North Sea
SAR	Search And Rescue
SD	Ship domain
SMS	Safety Management System
STPA	System-Theoretic Process Analysis
SVM	Support Vector Machine
TCPA	Time to Closest Point of Approach
TD-NLVO	Time Discrete Non-linear Velocity Obstacle
TDV	Time to Domain Violation
TRACEr	The technique for the Retrospective and Predictive Analysis of Cognitive Errors
UAV	Unmanned Aviation Vehicle
UNCTAD	United Nation Conference on Trade and Development
VCRO	Vessel Conflict Risk Operator
VHF	Very High Frequency
VO	Velocity Obstacle
VR	Virtue Reality
VTSO	Vessel Traffic Service Operator

Chapter 1 Introduction

Maritime transportation is one of the major contributors to the development of the global economy. With the growth of the global trade activities, however, the continuous occurrence of maritime accidents, especially ship collision accidents, has been posing a non-negligible risk to multiple aspects of the society due to its severe consequence in terms of human life, economic loss and environmental pollution, etc. This dissertation is devoted to proposing a novel approach of quantitative risk analysis methods on ship collision risk considering multiple sources of information, to obtain deeper insights into the characteristics of the risk and its evolution. In this chapter, the background of the topic is illustrated, together with the motivation of the research. The research questions, the contribution of the work, and the outline of the dissertation are also addressed.

1.1 Background and Motivation

Maritime transportation is one of the major contributors to the development of the world economy. According to the annual report of United Nation Conference on Trade and Development (UNCTAD), over 10.7 billion tons of cargo was transported via seaborne transportation in 2017, which has made the fastest growth in the previous five years by 4% (UNCTAD, 2018). To satisfy the continuously growing demand on global trade, the shipping activities, in the meantime, show great potential in growth.

However, with the rapid growth of global maritime activities, maritime accidents, especially navigation-related accidents, e.g. collision and grounding, etc. have been continuously posing a non-negligible risk to various aspects of the societies. The annual overview of maritime casualties by European Maritime Safety Administration (EMSA) illustrates that in 2016 there were 3145 marine casualties reported and “the combination of collision (23.2%), contact (16.3%), and grounding/stranding (16.6%) shows that navigational casualties represent 53.1% of all casualties with ships”(EMSA, 2018). Among these categories of accidents, ship collision, due to its high frequency and severe consequences in terms of loss of human life, economic loss, and environmental pollution due to potential spill of cargo and oil, has been drawing much attention from multiple stakeholders, e.g. Maritime Safety Administration (MSA), port authorities, shipping companies, ship designers, and the public, etc. One specific example of such accident is the collision between Iranian oil tanker “SANCHI” and Hong Kong bulk carrier “CF CRYSTAL” in the East China Sea on 6th Jan. 2018, which has caused “three crew of SANCHI died, and 29 were missing, and resulting pollution occurred. CF CRYSTAL sustained extensive structural damage to her bow and burn damage to other areas”(Maritime Safety Administration of China, 2018). At the same time, research and development on Marine Autonomous Surface Ship (MASS) have been drawing much attention from both academia and industry with its potential in improving the navigational safety and efficiency. However, since MASS is still at an early stage of its development, and there would be a transition period between conventional manned and autonomous shipping where the manned and unmanned ship could coexist in the traffic, the possible influence of applying MASS in maritime traffic on the risk of collision accident also needs to be explored and analysed to support the stakeholders to adopt risk mitigation measures. Under the call from the International Maritime Organisation (IMO) for a “safe, secure and efficient shipping on clean oceans”, much effort should be contributed to risk analysis and management of ship collision accidents to facilitate the safety management of maritime traffic in waterways.

Within this objective, many pieces of research have been devoted to proposing new methods and models to quantify the collision risk and obtain insights for risk analysis and mitigation. One of the classic frameworks for quantitative risk analysis for collision accidents is proposed by Fujii (Fujii and Shiobara, 1971) and Macduff (Macduff, 1974), which is expressed by Eq.1. 1:

$$P_{Collision} = P_{Geometric} \times P_{Causation} \tag{1.1}$$

Where the risk of collision is decomposed into two elements: 1) $\mathrm{P}_{\mathrm{Geometric}}$, which is the geometric probability of collision, also known as “Number of Collision Candidate”. It describes the probability or the frequency of the encounters between ships that have the potential for collision; and 2) $\mathrm{P}_{\mathrm{Causation}}$, which is the causation probability of collision. This element describes the probability of the dangerous encounters finally resulting in an accident, due to various contributors, e.g. mechanical failures, human errors such as fatigue and violation of navigation regulations, etc. With this design, various factors, e.g. maritime traffic situation, causal factors such as human failures, etc. can be considered in the process of risk analysis and can be reflected by the results to facilitate the decision-makers to propose risk mitigation measures.

Although the development of the research methods continues, there are some deficiencies in the current methods. For geometric probability, the focus is on the modelling of the encounter behaviour of ships with the parameters utilised for reflecting the navigational status of the ships and their spatiotemporal relationships. During this process, due to the understanding of navigation process and the choice of parameters, the results could be affected by the fluctuation of the indicators and the definition of the encounter process, which will introduce noise into the results and cause over/underestimation. For causation probability, the current modelling techniques consider the causation probability independent from the collision candidate analysis and ignore the influence of individual encounter information for each case. Much work should be conducted to integrate the two elements of collision risk analysis and provide information to facilitate the stakeholders of maritime transportation, e.g. MSA to obtain the insights of the risk level and facilitate the process of risk management.

To better assess the level of risk situation and quantitatively estimate the risk, a series of new methods for probabilistic risk modelling of ship collision accident with regards to the risk components following the classic framework is proposed, based on which, the analysis on the potential influence of MASS on collision risk can also be conducted. This dissertation is devoted to proposing new insights for probabilistic risk analysis of ship collision accident in waterways to facilitate the development of maritime safety research.

1.2 Research Questions

The objective of this research is to furtherly develop a quantitative risk analysis model for ship collision accident in waterways in an integrated manner that can introduce multiple sources of information into analysis and to further obtain insights of collision risk for safety management. To achieve the research objectives, one main research question has to be answered, which is:

> *How can a quantitative risk analysis method be designed for the risk of ship collision, considering multiple sources of traffic information, in order to obtain more insights into the factors contributing to collision risk, and eventually facilitate the safety of navigation in waterways?*

Current studies have deficiencies in integrating the elements of probabilistic risk analysis of ship collision, i.e. the estimation of geometric probability and causation probability is mutually independent. To further develop the quantitative risk analysis model, new approaches should be developed on both parts, which include:

1) Identification of the collision candidate among maritime traffic in waterways for a specific period with historical traffic data; and 2) Understanding of the mechanism of and contributing factors to ship collision, based on which, the causation probability should be obtained with the integration of individual encounter information. To answer the main research question and fulfil these functions, several sub-questions should be appropriately addressed:

Question on state-of-the-art:

1. *What methods have been proposed for quantitative risk analysis for ship collision risk, and what research gaps are to be explored to improve the research?*

Various methods and models have been proposed for the topic. The existing literature reviews have provided a general overview of the risk analysis methods for collision as a handbook. However, the technical characteristics and their trend of development are rarely discussed, e.g. criteria for collision candidate, etc. and their utilities for various stakeholders. To answer this research question, it is important to clarify the research background and motivation. Probabilistic risk analysis for ship collision is a broad and complicated topic, for which a clear analysis should be obtained. To address this sub-question, an extensive literature review is conducted.

Question on the geometric probability modelling for ship collision accident:

2. *How can an improved model be designed to identify and analyse ship encounters, and to obtain geometric probabilities of collision (number of collision candidate)?*

The essence of geometric probability modelling is to propose a method that can identify the ship encounters with the potential of a collision via the historical traffic data that can reflect the spatiotemporal relationships between ships and their trend of development. Currently, studies focusing on geometric probability usually introduce traditional CPA analysis(Zhen et al., 2017), statistical estimation (Pedersen, 1995), ship-domain-based (Chai et al., 2017; Szlapczynski and Szlapczynska, 2017b) and indicators based-(relative distance, speed, etc.) detection methods (Zhang et al., 2017). However, such works ignore that ship encounter is a dynamic process, in which first ships approach closer and finally depart from each other; moreover, due to the movement between the own ship and the targets, the indicators that reflect the spatiotemporal proximity may fluctuate, and influence the results of identification. During the process of encounter, the spatiotemporal relationship between ships could fall into a dangerous situation which has the potential of collision. Such a situation should also be a process which is part of the whole encounter. The answers to this question are to propose a method that can identify a collision candidate from the perspective of the encounter process.

Question on the causation probability modelling for ship collision accident:

3. *How can the causation probability model be designed under limited data availability and be integrated with the encounter situation information?*

Causation probability modelling for ship collision is to identify and analyse the accident contributing factors and their causal relationships, based on which the mechanism of failure caused by these factors can be obtained, together with the quantified probabilistic risk of the accident. However, during the modelling process, due to the limited sources of accident data, expert knowledge and accident investigation reports are often required for obtaining the causation probability. During this process, it becomes difficult to model the causation probability due to the uncertainty induced by limited information. To address this research question, several sub-questions should be included: 1) What factors should be considered when analysing collision risk from causation perspective? 2) How to determine the causal relationships between contributing factors? 3) From which sources can the data be collected? and 4) How to alleviate the uncertainty during the process? The answers to this research question are to establish a causation probability model that can perform imprecise inference with limited information and integrate the individual encounter information into the process.

Question on the potential influence of Maritime Autonomous Surface Ship (MASS) on the risk of collision in waterways:

4. *What encounter situations could occur in waterways? What could be the influence on the risk of collision in waterways with different levels of autonomy of MASS, and what could be the critical components of MASS from a safety perspective?*

As many researchers have argued that human and organisational factors are one of the major contributors to the occurrence of a maritime accident (Ren et al., 2008). Recently, with the rapid development of modern technology, MASS has been drawing much attention from both academia and industry due to its great potential in improving the navigation safety by reducing or removing the influence of human errors. Li, et al. (Li et al., 2019), Xie, et al. (Xie et al., 2019), and Chen, et al. (Chen et al., 2019a) proposed series of models for multi-ship collision avoidance scenarios of MASS using Model Predictive Control (MPC)-based approaches. Similarly, Zheng, et al. (Zheng et al., 2018) proposed a distributive control method for waterborne Autonomous Guided Vessel (AGV) groups considering the cost efficiency during operation. These works provided profound references for the future design and control method of MASS to improve the safety level of their operations. However, as for the perspective of risk analysis and management of maritime traffic, there are few researches on the potential influence of introducing MASS in the estimation of collision risk in waterways. Besides, since currently there is no clear and commonly accepted design of the MASS system in the industry, it is difficult to establish a risk analysis model which can precisely reflect the component of this system and quantitatively measure their risks. To work towards facilitating the stakeholders, e.g. port authorities to understand the possible risk level when MASS was implemented and adopt proper regulations for safety management in the area, the research method in our work focuses on the insights obtained from the comparison between Market Penetration Ratio (MPR) and the level of autonomy of MASS under the framework of collision risk analysis. The answer to these questions is to perform a risk analysis of MASS on collision risk following the above-proposed framework and evaluate the potential primary choice of system configuration of MASS.

1.3 Contribution

The results of this research is a series of risk analysis methods for ship collision accidents in waterways, in regards to geometric and causation probability analysis with multiple sources of information. The contributions of this dissertation are as follows:

1. A comprehensive review of risk analysis for ship collision accidents

Risk analysis for ship collision accident is a classic problem with a long history and much attention from both academia and industry. However, there is a lack of literature that depicts the development of its research methodology, the role of the stakeholders, the connections between various risk analysis techniques, and the organisation of this knowledge in a more structured manner. In this research, an extensive review of collision risk analysis in maritime traffic will is conducted to obtain such a picture.

2. New insights into collision candidate detection

Traditionally, methods for detecting collision candidates and estimate geometric collision probability have strong connections with risk detection methods for individual ships, which is determined by either CPA (Closest Point of Approach) and its parameters, or by using the violation of ship domain or similar concepts. When introducing these methods for candidate detection, the parameters within algorithms, e.g. time interval for detection, shape and scale of ship domain, etc. always influence the reliability of the results. This research introduces the velocity obstacle algorithm and considers the whole ship encounter procedure as a detection object in order to diminish the influence of the fluctuation of the traditional indicators.

3. New insights into causation modelling of ship collision accident

The maritime traffic system is a complex social-technical system. An accident can be regarded as "a result of complex, at least partially unknown interactions in the system."(Hanninen, 2014). In this research, accident contributing factors from the operation perspective of ship navigation and collision avoidance procedure will be identified; this includes multiple aspects, e.g. machinery failures, human and organisation factors, communications errors, etc. Together with individual encounter information, a credal network-based model will be established to infer the accident causation probability under uncertainty. In this manner, the mechanism of the accident will be further explored.

4. New insights into the possible influence of MASS on collision risk in maritime traffic

With the rapid development of new technologies such as Artificial Intelligence (AI), robotics and control theory, etc. the autonomy of ships is considered a promising approach to improve the safety and efficiency of the maritime transportation system, as it may exclude the potential failures induced by human errors. Out of this perspective, various projects about autonomous ship have been undergoing to demonstrate such a potential, e.g. ÄlyVESI - Smart City Ferries project (Valez Banda Osiris A and S, 2019), Online risk management and Risk Control for Autonomous Ships (ORCAS) project (Utne et al., 2020), Maritime Unmanned Navigation through Intelligence in Networks (MUNIN) project (Fraunhofer, 2016; Rodseth and Burmeister, 2015), etc. However, due to the fact that the design and development of MASS are still at the early stage, they are more focused on an individual ship perspective. The potential influence of the introduction of MASS on the risk of collision in maritime traffic is rarely discussed. In this research, the potential encounter situation in maritime traffic with different MPR of MASS are explored, together with the influence of MASS on the causation probability of ship collision considering different scenarios of ship autonomy. In this manner, the potential influence of MASS on collision risk from the macroscopic perspective can be analysed, as a dedicated case study of the potential of this new method, not only for convenience but also for autonomous ships.

1.4 Outline of the Dissertation

This dissertation contains six chapters which contribute to the establishment of the quantitative risk analysis method for ship collision accident in waterways. Figure 1.1 illustrates the structure of the dissertation.

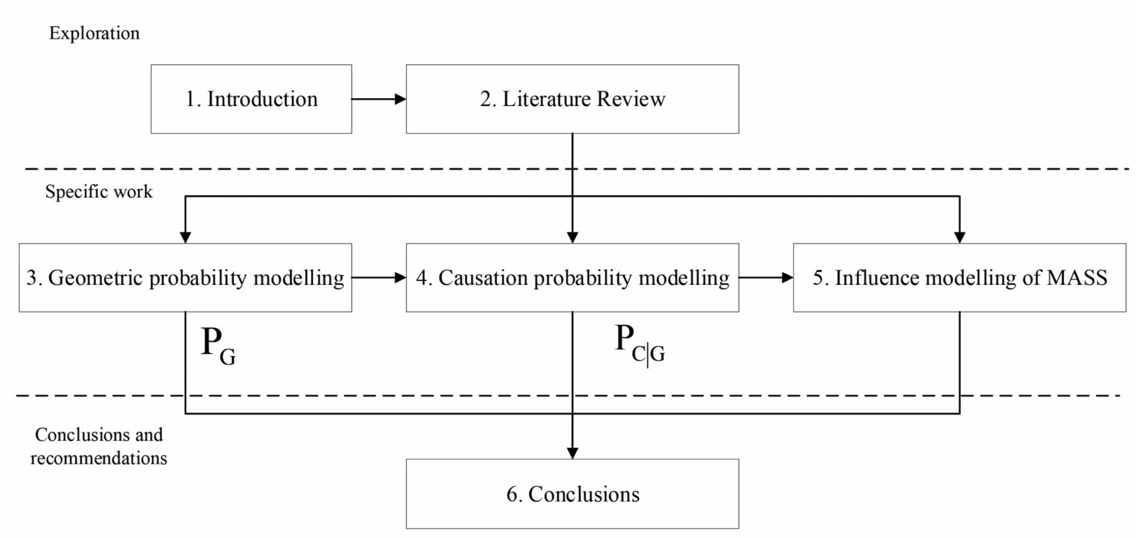

Figure 1.1 Structure of the dissertation

Chapter 1 illustrates the background of maritime traffic and the motivation of this research. The research questions on proposing the quantitative risk analysis models, the contributions of the research and the outline of the dissertation are also illustrated.

Chapter 2 presents a comprehensive state-of-the-art on the current development of risk analysis methods for ship collision accident, where two dimensions are discussed: 1) The stakeholders on collision risk, and their interests are extensively discussed; and 2) The current methods for collision risk research are reviewed and analysed following the classic framework. Then the characteristics of the methods, their advantages and disadvantages are discussed, together with the research gaps in collision risk analysis.

Chapter 3 focuses on the establishment of methods for collision candidate detection. The essence of this chapter is to model the spatiotemporal relationship between ships with known traffic data, i.e. ship Automatic Information System (AIS) data. The Non-Linear Velocity Obstacle (NLVO) method is introduced as the fundamental approach. Several case studies are conducted to demonstrate the effectiveness of the methods. Comparisons between other classic collision candidate detection methods are also conducted to illustrate the advantages of the proposed method.

Chapter 4 focuses on the modelling of causation probability of ship collision accident. The accident contributing factors are identified based on the historical accident investigation report, following the structured framework of Human Factors and Classification System (HFACS). The Credal Network (CN), which is an extension of Bayesian Network (BN) model is introduced to conduct the probabilistic inference under uncertainty and obtain the results of causation probability as intervals. The individual encounter information is then integrated into the structure of the model to enable its capabilities on considering the encounter situation when modelling. A case study is conducted to verify the proposed method and analyse the influence of contributors on the occurrence of the accident.

Chapter 5 probes the potential influence of introducing MASS into the maritime transportation system. The analysis is conducted following the previously proposed new framework of risk analysis. Different MPRs of MASS are considered in order to probe the possible encounter scenarios in the traffic, specifically, the encounter types and their percentage in the total collision candidate. Several levels of autonomy are considered. Combining the two aspects, the potential influence is analysed, together with the identification of the critical components on different levels of MASS.

The major findings and conclusions are summarised in chapter 6, which conclude the answers to the research questions proposed in Chapter 1.

Chapter 2 State-of-the-art of Probabilistic Collision Risk Analysis

To analyse and estimate the risk of ship collision accident in waterways, various methods and models have been proposed with the development of the technology and understanding of maritime traffic. However, as the maritime transport system is a complex system where multiple stakeholders participate, their interests vary among them; hence the applicability of the methods are different. Besides, there is a lack of structured analysis on the development of the quantitative risk analysis method for ship collision, which is of great necessity to identify the deficiency in current research and facilitate the peer researchers in proposing new ideas and methods. In this chapter, an extensive literature review on the state-of-the-art of the development of collision risk modelling is presented. The review focuses on two dimensions: 1) Stakeholders on the risk of ship collision accident and their interests and corresponding risk analysis methodology; and 2) Development of risk analysis methods following the classical framework. In the end, a comprehensive discussion on the relations of collision risk analysis for individual ship and macroscopic risk analysis, comparison among the collision candidate detection methods are presented.

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2.1 Introduction

To analyse and model the risk of ship collision accident in waterways, various methods and models have been proposed to obtain the insights about the following questions: 1) What is the risk level of the accident in the area? 2) Which aspects or indicators should be considered in the analysis? and 3) Based on the results, what risk mitigation should be proposed, which can be effective in managing the risk? However, as risk is a very broad concept, there are many definitions of risk that can be found in literature, which defines and measure risk from different perspectives. Kaplan (Kaplan, 1997) proposed that when people talk about risk, three critical elements involve: “Scenario”, “Likelihood”, and “Consequences”. This argument describes the risk from the three aspects: 1) The accident (scenario); 2) The probability of the accident (likelihood); and 3) The consequence due to the occurrence of the accident, which is comprehensively based on the understanding of the accident and its potential influence.

In practices, the understanding of risk often varies when it comes to different stakeholders and implication of risk reduction measures. As for the maritime transport industry, Literatures (Goerlandt and Montewka, 2015b) has conducted a comprehensive review of the fundamental issue of risk analysis in the maritime transportation system. From the reviews, one can see that the definition of risk varies from one to another. From the engineering perspective, the risk is often considered a product of probability and the potential consequence of hazardous event (Kristiansen, 2005), i.e. risk is the probability of the undesired event and its consequence. In the maritime field, however, due to the rare occurrence of accident and insufficiency of accident data, quantifying the consequence of a maritime accident is always difficult. Therefore, considerable efforts have been put into research on probability of ship collision accident since reducing such probability is the most cost-effective method to reduce risk (Pedersen, 2010).

In this research, we accept such definition while the focus is on the methods to obtain the probability of the occurrence of collision in certain regions, e.g. ports and waterways, etc., and methods for providing information for risk identification, quantification, and management for various corresponding stakeholders. Compared with the perspective which focuses on risk analysis for collision avoidance for individual ships, such perspective is defined as the macroscopic perspective of collision risk analysis.

Probability-based risk analysis of ship-ship collision has received growing attention from academia since it provides concise and quantitative results for risk assessment and mitigation in combination with the estimation of consequence. Several scholars have done reviews on the maritime accident analysis concerning ship-ship collision, which can be classified into two major categories: 1) Review/Overview of research methods and 2) Review on fundamental concepts in maritime risk analysis research. Focusing on the methods introduced into the research, Li et al. (Li et al., 2012) offered a detailed review of maritime traffic risk analysis from the perspective of frequency and consequence estimation, respectively. Lim et al. (Lim et al., 2018) provide a general overview on the development of models and algorithms in terms of their methodology, contribution, assumptions, etc., based on a survey of literature concerning maritime risk analysis. Goerlandt and Montewka (Goerlandt and Montewka, 2015b) performed a literature review where the definition, perspectives of risk and corresponding applications are well elaborated. Besides, the reliability and validity issues of ship-ship collision risk analysis methods, such as the sensitivity of model results in regard of choice of model parameters are analysed and identified by Goerlandt and Kujala (Goerlandt and Kujala, 2014).

The existing literature reviews have provided a general overview of the risk analysis methods for collision as a handbook. However, these reviews rarely discuss the technical characteristics, e.g. criteria for collision candidate, etc. and their utilities for various stakeholders. Moreover, with the fast development of new technologies such as AIS, artificial intelligence, etc., more new methods and approaches have been proposed recently, which are not included and compared in previous reviews.

Out of these motivations, to better understand the methodological overview of this topic and their inter-methodological relationships, a comprehensive comparison between different probabilistic risk analysis of ship-ship collision is needed. This review aims to provide a broad and structured analysis of the current literature on risk analysis of ship-ship collision accident from a macroscopic perspective, to clarify the methodological development of risk analysis on ship-ship collision accident for different stakeholders, and to discuss the technical characteristics and the relationships in terms of methods of them with respects to various risk analysis scenarios. Ultimately, we hope that a good reference can be provided to the researchers to make further contributions to the industry.

2.2 Scope and Review Methodology

As for the research on the probability of ship collision accident, the framework proposed by Fujii and Shiobara(Fujii and Shiobara, 1971) and Macduff (Macduff, 1974) has been widely applied, which is:

$$P_{Collision} = P_{Geometric} \times P_{Causation} \tag{2.1}$$

According to Eq. 2.1, the probability of ship-ship collision is decomposed into two elements: 1) Number of collision candidates, also known as "geometric collision probability" (Fujii and Shiobara, 1971) and, which describes the probability of ships in encounter that has potential of collision in the assessed region, or the frequency of collision candidates within specific time. Such encounter is also known as near-miss (e.g. (Zhang et al., 2016), etc.) in academia and practices; and 2) Causation probability, which describes the probability of collision due to failures from various aspects, e.g. human reliabilities, human and organisational factors, mechanical failure, etc. According to the literature (Chauvin et al., 2013; Martins and Maturana, 2010; Ren et al., 2008), human and organisational factors are one of the major contributors to the marine accident. These factors, e.g. decision error, violation of the regulation, fatigue, etc. and their causal relationships together contribute to the collision. In this manner, both the maritime traffic information and accident causations are taken into consideration in addition to historical accident data and investigation reports.

To collect the related literature for the review, two steps of literature survey were performed. "maritime accident", "marine accident", "ship collision", "vessel collision", "risk analysis", "risk assessment", "accident analysis", "maritime traffic", "marine traffic", "ship traffic", and "vessel traffic" are chosen as keywords for topics in databases of "Web of Knowledge[1]" and

[1] http://apps.webofknowledge.com/UA_GeneralSearch_input.do?product=UA&search_mode=GeneralSearch&SID=6CfGfBuQT8xP8ugjSBu&preferencesSaved=

"ScienceDirect[2]" as the first step to collect relevant researches. The literature searching was finished on Feb 1st, 2019. Based on the records extracted from the databases, all the title and abstracts are examined thoroughly to filter further out references which are not closely related to the topic. Figure 2.1 indicates the survey procedure. After two rounds of literature surveys and snowballing from the reference within these works, 301 pieces of record are obtained, among which 275 full texts were retrieved, including journal chapters and conference proceedings. Based on the collected literature, a selection process was conducted according to the following criteria: 1) Does the literature related to probabilistic risk analysis of ship-ship collision accident? 2) Does it include the methods that can be utilised to facilitate research on either one of the components in Eq. 2.1 or both? Moreover, 3) From the methodology perspective, is it representative to reflect the new methodology on PRA of ship-ship collision accident, or the application of collision risk analysis in different areas? One hundred twelve articles which contain approaches for research under Eq. 2.1, support the arguments or are representative of the topic are included in this manuscript.

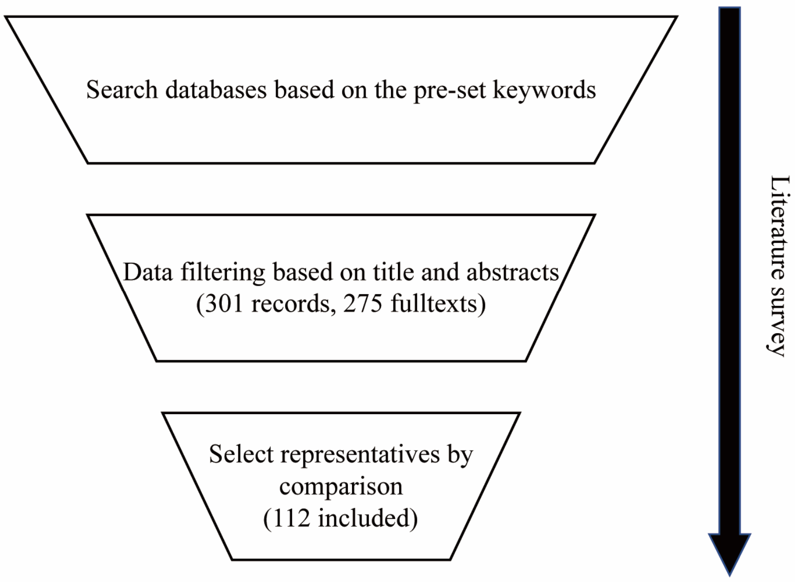

Figure 2.1 Procedure of literature survey

Based on the collected materials, the literature review is conducted with respect to two dimensions: 1) **Stakeholder.** As is well acknowledged, the goal of risk analysis is to support the decision-making process. The maritime transportation system is a complex system where multiple stakeholders (ship, port, etc.) are highly involved. The interests of concern vary significantly among them. Focuses and technical approaches to collision risk analysis are therefore adapted to various needs. In this chapter, individual ships and maritime safety administrations, or port authorities are included as representatives of the component and system level of the maritime traffic system, respectively. Therefore, the stakeholders and their corresponding interests of concern will be analysed. 2) **Methodology.** Multiple theories, approaches and models are introduced into the risk analysis on maritime accident during the late 40 years. These studies are either highly case-dependent or generalized methods that can

[2] https://www.sciencedirect.com/

be implemented in similar situations. To obtain a well-structured overview of the technical development, approaches that are utilised in the literature will be classified into different groups based on their technical characteristics. Their inter-methodological traits, advantages, and disadvantages for application in different scenarios will be analysed and identified.

With the two dimensions of literature review, the focus of this chapter is on reviewing the methods utilised to obtain the quantitative probability of collision accident from the macroscopic perspective; therefore, the fundamental concepts about risk are not discussed, either the methods for collision avoidance of individual ships. The literature concerning probabilistic risk analysis of ship-ship collision is collected and reviewed from both the area of application and technical methods. A classification structure based on the methodological approaches of risk quantification and criteria utilised in each research methods is established.

2.3 Stakeholders

The maritime transportation system is a complex system where multiple stakeholders are making contributions to the safety and efficiency of the system. Among them, individual ships and maritime safety administrations can be considered as major participants representing the component and system level of the maritime traffic system. The interests of concerns of each part may vary from one to another, hence the methods and focus on collision risk may also be different. Therefore, it is reasonable to have an overview of what are the concerns of each counterpart reflected by the literature.

2.3.1 Maritime Safety Authority

Maritime safety authority or maritime safety administration is the official administration responsible for the embodiment of maritime safety under their authority. Because of the role that maritime safety authority plays in the system, the risk of ship-ship collision is frequently considered from the macroscopic perspective. Risk analysis on ship-ship collision usually serves as a tool to understand the current risk level from the management perspective, and to evaluate the performance of the regional authorities (Mou et al., 2019).

In literature, the interests of concern for risk analysis for maritime safety authority are as follows:

1) The frequency of accident occurrence and near misses

For maritime authority, maritime traffic accident will directly diminish the safety level within their authority, resulting in potential loss of life, economic loss, and environmental consequences. This, in turn, will reduce their performance impression to the public. Besides, the ship encounters that have potential for collision and undesired consequences, and yet did not lead to the actual collision are also of great interest to the MSA. Such encounter is often defined as near misses, or collision candidates, which have drawn much attention from academia and practices, e.g. (van Westrenen and Ellerbroek, 2017; Zhang et al., 2016), etc. Together with other Key Performance Indicators (KPI), these indicators play an important role in maritime safety management (Valdez Banda et al., 2016b). To maintain the maritime safety, many scholars have conducted frequency of accident analysis using historical data analysis, statistical regression, stochastic process analysis, etc. to facilitate authorities to identify areas of high risk both in the spatial and temporal dimension, which will provide strong references for the proposal of safety regulations.

2) Potential consequence

A collision between ships can result in severe consequences, e.g. the collision accident between Iranian oil tanker “SANCHI” and bulk carrier “CF CRYSTAL” caused “three crew of SANCHI died, and 29 were missing, and resulting pollution occurred” (Maritime Safety Administration of China, 2018). The environmental consequence is another focus of maritime safety authority which cannot be ignored, among which oil spill after collision and grounding is one of the hot topics in academia and practices, e.g. Yu et al. (Yu et al., 2018) and Amir-Heidari and Raie (Amir-Heidari and Raie, 2018) conducted a probabilistic risk assessment of accidental oil spill in Bohai, Chain and the Persian Gulf, respectively. Goerlandt and Montewka (Goerlandt and Montewka, 2014; Goerlandt and Montewka, 2015a) conducted utilised Bayesian Network approach to model risk of the oil spill from product ship and tanker due to collision accident, respectively. Together with research on the occurrence of a ship-ship collision accident, research on consequence estimation and response can facilitate maritime authorities to obtain a comprehensive impression of current risk level, to have comprehensive estimation and management on the possible environmental consequence (Helle et al., 2015), and to have good knowledge on the preparedness of emergency reaction.

3) Human and organisational factor

As is well known that human and organisational factors are one of the major contributors to the marine accident(Chauvin et al., 2013; Macrae, 2009; Ren et al., 2008), e.g. Decision error, violation of regulations, etc. (Chauvin et al., 2013). The collision between ships also shares this trend. For maritime safety administration, one of their responsibility lies in the examination and certification of the ship crew. Which drew attention from maritime authority to human reliability and human and organisational factors in the collision accident. Table 2.1 illustrates the sources to have a general overview of the literature focus on interests of concern:

Table 2.1 Methods for estimating collision probability from MSA perspective

Interests of Concern	Sources
The frequency of accident occurrence	(van Westrenen and Ellerbroek, 2017; Zhang et al., 2017; Zhen et al., 2017)
	(Chai et al., 2017; Cucinotta et al., 2017; Grabowski et al., 2000; Merrick et al., 2002; Silveira et al., 2013; van Dorp et al., 2001; Weng and Xue, 2015; Wu et al., 2016; Zhang et al., 2016)
Potential consequences	(Goerlandt and Montewka, 2014; Goerlandt and Montewka, 2015a; Grabowski et al., 2000; Gucma and Bak, 2016; Merrick et al., 2002; Montewka et al., 2014; van Dorp et al., 2001)
Human reliability, Human and organisational factors	(Sotiralis et al., 2016; Yıldırım et al., 2019; Zhang et al., 2013; Zhang et al., 2018b)
	(Grabowski et al., 2000; Merrick et al., 2002; Uğurlu et al., 2013; van Dorp et al., 2001)

2.3.2 Individual Ship

Individual ship plays as the cornerstone of the maritime transportation system. Keeping ship navigating in a safe and good situational awareness throughout the voyage are the paramount objectives for Officers on Watch (OOW). Risk analysis of collision between individual ships focuses on facilitating an individual ship to understand the potential collision and facilitate possible collision avoidance operations and control measures. Based on the literature collected, the interests of concern for individual ships concerning collision risk are as follows:

1) Risk detection

Obtaining clear consciousness about the risk of collision is of great importance to individual ships. To do that, various methods have been proposed, which takes immediate or projected proximity level in the spatiotemporal domain, etc. as indicators.

2) Conflict resolution

After the detection of collision risk, the main objective for an individual ship would be conflict resolution, which means the decision making and execution for collision avoidance behaviour. From the literature, we can find that most research on collision risk from an individual perspective has a focus on this part, among which ship manoeuvrability and control, knowledge-based decision making, etc. have been introduced.

2.3.3 Ship Designer

In recent years, the concept of risk-based ship design has been drawing attention from research in disciplines such as ship design, operation, and regulations (Breinholt et al., 2012). The idea of risk-based design is to integrate risk-based approach, e.g. quantitative risk assessment, etc. into the ship design process to propose an innovative design or improve the current design concerning safety while considering the efficiency and performance (Papanikolaou, 2009). Based on the literature collected, the interest of concern for ship designers are as follows:

1) Design

The design is of critical importance to the safety of the ship and the foundation of its whole life operation. For risk-based ship design, structural reliability, damage stability, component and system reliability, etc. are of great significance for the safety of navigation and crashworthiness. To do this, various approaches have been proposed, e.g. impact scenario analysis (Stahlberg et al., 2013), etc. For interested readers, detail reviews and methods can be found in the literature (Deeb et al., 2017; Liu et al., 2018; Pedersen, 2010)

2) Operation

Risk-based ship operation focuses on improving the performance of OOWs to implement safe navigation and preventing the accident. To do this, ergonomics, innovative bridge and overall ship design, etc. are introduced to improve the performance of OOWs, hence the safety of the ship. e.g. Montewka et al. (Montewka et al., 2017) quantified the effects of noise, whole-body vibration, and ship motion on OOWs' performance, which can be incorporated into risk-based ship design. Sotiralis et al. (Sotiralis et al., 2016) established a Bayesian network-based model for ship collision accident, where human operation and performance under different working situations are well integrated.

3) Regulation

As proposed in (Papanikolaou, 2009), instead of prescriptive regulation after the occurrence of the accident, the tendency of goal-based standard and risk-based regulation have become clearer. The goal of such regulations is to provide a regulatory framework, e.g. risk evaluation criteria, etc. to facilitate the risk-based design. One of the representatives of such a framework is Formal Safety Assessment (FSA) (IMO, 2018a), which is proposed by IMO as guidelines to systematically assess new or existing regulations for maritime safety and environmental protection.

2.3.4 Other Stakeholders

As aforementioned, the maritime traffic system is a complex system where multiple stakeholders participate in. Besides the three representative stakeholders mentioned in the previous sections, various more also contribute to the safety of maritime transport from different aspects, e.g. shipping companies, insurance companies, Search And Rescue (SAR) departments, etc. However, since this chapter is to collect and review probabilistic risk analysis and management on the occurrence of a ship-ship collision accident, details about these stakeholders will not be further discussed.

2.4 State-of-the-art methods

2.4.1 Brief Overview

Research on risk analysis of ship-ship collision for different stakeholder usually concerns three elements: the probability of an accident, potential consequences, and human and organisational factors of ship collision. Probability is one of the most common indices to reflect the risk of ship-ship collision. Among the literature, the probability of ship-ship collision is estimated via two technical approaches: 1) Statistical estimation approach and 2) Synthetic estimation approach.

For statistical estimation, historical accident and traffic information within certain waterways are collected as data sources, and techniques such as statistical analysis, regression, artificial intelligence (neural network, support vector machine, etc.), etc. are introduced to estimate the probability of an accident. For the synthetic approaches, the probability of collision is estimated according to the framework proposed by Fujii and Shiobara (Fujii and Shiobara, 1971) and Macduff (Macduff, 1974), which has won the popularity for a long period. In this way, both the maritime traffic information, e.g. dynamic information of ship movements and accident causation factors, e.g. human and organisational factors, external factors are taken into considerations.

Combining the two major categories, we have identified methods that are frequently used in estimating the probability of ship-ship collision from the macroscopic perspective, to the best knowledge of us. Table 2.2 illustrates the results and a detailed description of the approaches will be given in the following section. An overview of the examples on probabilistic risk analysis of ship collision accident can be found in Appendix I.

Table 2.2 Methods for estimating collision probability from the macroscopic perspective

Method	Description	Sources
Statistical analysis	Perform statistical analysis of historical accident data, methods such as regression, artificial intelligence are introduced.	(Grabowski et al., 2000; Kristiansen, 2005; Kujala et al., 2009; Merrick et al., 2002; van Dorp et al., 2001)
Geometric collision probability analysis	Design a mathematical model to identify potential collision candidate base on traffic statistics	(COWI, 2008; Lusic and Coric, 2015; Pedersen, 1995)
	Ship domain-based collision candidate identification	(Chai et al., 2017; Szlapczynski and Szlapczynska, 2016; Weng and Xue, 2015)
	Indicator-based collision candidate identification (e.g. relative speed, bearing, etc.)	(Qu et al., 2011; Zhang et al., 2017)
Causation collision probability analysis	Statistical analysis of historical accident data	(Kujala et al., 2009; Mou et al., 2019)
	Fault Tree analysis to obtain the causation probability	(Martins and Maturana, 2010; Pedersen, 1995)
	Bayesian Network to incorporate multiple sources of information, e.g. historical data, expert knowledge, etc.	(Harrald et al., 1998; Martins and Maturana, 2013; Montewka et al., 2014; Montewka et al., 2017; Trucco et al., 2008)
	Human reliability analysis and Human and organisational factors analysis	(Harrald et al., 1998; Martins and Maturana, 2013; Montewka et al., 2017; Sotiralis et al., 2016; Ung, 2015; Valdez Banda et al., 2015; Xi et al., 2017)

To estimate probability by statistical analysis of historical data, techniques such as regression(Yip, 2008), synthetic aggregation (Christian and Kang, 2017), etc. were introduced.

For geometric probability, various methods have been proposed in the literature. From the perspective of criteria for collision candidate detection, this group of research can be classified into the following groups: 1) CPA-based approach; 2) Indicator-based criteria; 3) Safety boundary-based criteria, and 4) Velocity-based criteria; the details of each criterion will be illustrated in section 2.4.2.

Causation probability is another critical element for probabilistic risk analysis. It describes the probability that a ship will collide due to factors such as human errors, mechanical failure, external elements (rough sea, high wind, etc.), etc. As aforementioned, human factors are one of the major contributors to the occurrence of collision accident (Chauvin et al., 2013; Martins and Maturana, 2010; Ren et al., 2008). Research on human reliability (Groth and Swiler, 2013) has provided effective and efficient tools to facilitate causation probability research from multiple aspects, e.g. human factors determination and classifications, causation relationships determinations, etc. To obtain the causation probability, the following techniques were introduced, which will be illustrated in section 2.4.3 in detail: 1) Statistical analysis of historical accident data, e.g. (Kujala et al., 2009); 2) Fault Tree Analysis and Event Tree, e.g. (Martins and Maturana, 2010); 3) Bayesian network, e.g. (Goerlandt and Montewka, 2015a; Sotiralis et al., 2016).

2.4.2 Geometric Probability

Geometric probability, also known as the number of collision candidates, is the first step for probabilistic risk analysis on ship-ship collision using Eq. (2.1). It describes the number of ships encounters which have the potential for collision and undesired consequences. Such an encounter is also defined as near-miss in many research and practices. In this section, the majorities of approaches for the geometric probability of ship-ship collision are collected and elaborated.

1) Synthetic Indicator Approach

For synthetic indicator approach, variables that can reflect spatiotemporal relationships between ships are often selected to construct criteria for the task. Closest Point of Approach (CPA) and its parameters: DCPA, which means the closest distance between two ships and TCPA, which is the time left to the CPA point (see Figure 2.2), are important parameters for OOW to determine whether the risk of collision exists and the urgent level of the situation. It indicates the linear projected spatial and temporal proximity between ships under the **assumption** that own ship and target ships maintain their kinematic status (speed, course, etc.) during the encounter situation.

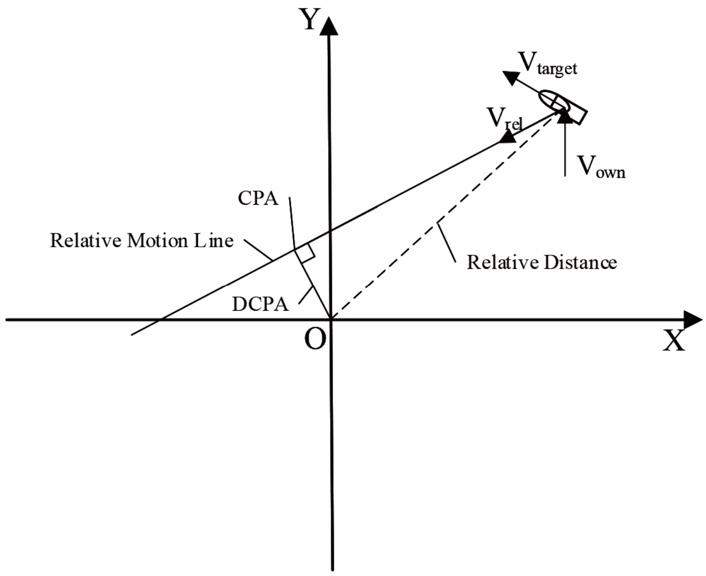

Figure 2.2 CPA and its parameters

For individual ships and maritime safety operators, if the measured value of CPA by facilities such as AIS, ARPA radar etc. is smaller than a pre-set threshold, a warning will be given to the OOWs, and possible collision avoidance suggestion could also be proposed. Such parameters are usually utilised in two manners: 1) Criteria for collision candidate detection, which is the same as individual risk analysis. And 2) Synthetic proximity measurement with a combination of D/TCPA in the form of $f(\text{TCPA, DCPA, ...,})$. A numeric value will be obtained according to the function, which will be utilised as an indicator of risk. Thanks to the simplicity, such method has won popularity in the practices of risk analysis and avoidance of ship collision, e.g. (Wang et al., 2017), especially with the help of Automatic Radar Plotting Aid (ARPA) (Bole et al., 2014).

Directly analysing indicators that can reflect their spatiotemporal relationship is another approach. Distance, absolute/relative speed, course, heading, etc. are usually utilised as indicators to measure proximity level between ships. Series of functions are established upon these indicators, e.g. inverse proportional function (Zhang et al., 2015b), etc. By incorporating these indicators as risk function, a numerical value can be obtained, which reflects the risk level of the current situation. However, as this approach considers multiple factors, the meaning of the results is not as explicit as that from CPA-based approaches. When determining the risk of collision among ships, such results usually serve as comparable values to determine which encounter is more dangerous than others.

Many pieces of literature can be identified that utilised these approaches to detect collision candidates with various sources of information. Table 2.3 gives an overview of the literature identified, followed by the detailed introduction of each work:

Table 2.3 Sources of literature for synthetic indicators

Parameters utilised	Sources
T/DCPA	(Bukhari et al., 2013; Debnath and Chin, 2010a, 2016; Debnath et al., 2011; Mou et al., 2010; Zhang et al., 2015a; Zhen et al., 2017)
Distance, absolute/relative speed, course, heading, etc.	(Li et al., 2015; Zhang et al., 2016; Zhang et al., 2015b; Zhang et al., 2017)

As for the application of CPA in collision risk analysis, many examples can be found in literature: Bukhari et al. (Bukhari et al., 2013) introduced fuzzy logic as an instrument to process DCPA and TCPA values to determine collision danger from the perspective of Vessel Traffic Service Operator (VTSO). Zhen et al. (Zhen et al., 2017) developed a real-time collision risk measurement model for maritime traffic surveillance. Encounters with high potential for a collision can be identified by risk function which utilises TCPA and DCPA as variables. Among these works, the collision candidate is determined based on the threshold of CPA parameter or its combination.

Following another approach, Mou et al. (Mou et al., 2010) proposed a dynamic collision risk model for waterways based on Safety Assessment Model for Shipping and Offshore on the North Sea (SAMSON) model by incorporating exponential function of DCPA and TCPA of ships, where CPA values of encounters are introduced to incorporate with static probability of collision to assess encounters. Debnath et al. (Debnath and Chin, 2010a, 2016; Debnath et al., 2011) developed Navigational Traffic Conflict Technique (NTCT) by estimating the risk of in fairways where a truncated gamma distribution of maximum value of DCPA and TCPA between ships is estimated as one of the critical elements of the risk formula.

For research directly utilising distance and other variables to assess encounter situation, works by Zhang et al. (Zhang et al., 2016; Zhang et al., 2015b; Zhang et al., 2017) are one of the representing researches. The distance between ships, relative speeds, course difference, etc. are incorporated as a function, which is defined as Vessel Conflict Risk Operator (VCRO). The distance between ships and domain contour are added afterwards as the improvement that considers ship domain. One of the functions utilised in these works is shown in Eq. 2.2:

$$VCRO \sim \left(\left(x - l_{\alpha} \right)^{-1}, y, g\left(z \right) \right) \tag{2.2}$$

where x is the distance between two ships; l_{α} is the distance between target ship to the safe boundary of own ship; y is the relative speed, and z is the phase which indicates the relative angle between two ships.

Besides, Li et al. (Li et al., 2015) developed navigational traffic conflict technique to identify ships in a conflict encounter situation, where relative distance, bearing, relative speed, course, DCPA, and TCPA are considered indicators to construct the classification model. A Support Vector Machine (SVM) was trained to identify collision candidates with new data. Hilgert and Baldauf (Hilgert and Baldauf, 1997) utilised CPA parameters and actual distance as indices to determine the risk of collision by comparison with limit values.

For individual ships, synthetic indicator approach is often utilised as a decision-support tool to analyse the encounter situation and support collision avoidance. Zhang et al. (Zhang et al., 2015a) developed a distributed collision avoidance supporting system with the integration of ship manoeuvrability model and COLREGs, taking CPA and its parameters as indices of collision risk. Goerlandt et al. (Goerlandt et al., 2015) integrated CPA parameters and expert knowledge to propose a framework of risk-informed collision alerting system. Ozoga and Montewka (Ozoga and Montewka, 2018) proposed a multiple encounter collision risk analysis and visualisation method for individual ships by integrating CPA parameters, ARPA system with multiple sources of information, to support collision avoidance in heavy traffic basins.

Among the literature, one can find strong similarities between collision risk analysis for individual ships and macroscopic research, e.g. risk analysis for ports and waterways. However, since the status of ships during the encounter is continuously changing, the assumption that their kinematic status remains unchanged could result in detection errors.

2) Safety boundary approach

Besides synthetic indicator approach to detect collision candidates and estimate the risk of such event, approaches that introduce spatial boundary to reflect spatial relationships between ships are also introduced, among which collision diameter and ship domain are two important concepts frequently introduced in research. In this section, the details and applications of the two concepts are discussed.

Collision Diameter

To estimate the number of ship-ship collision in Japanese waters, Fujii and Shiobara (Fujii and Shiobara, 1971) first proposed the concept of Collision Diameter (CD). According to the definition, CD is a safety boundary utilised to analyse collision candidates and risk of collision, which is shown in figure 2.3. It describes the minimum area around the ship to avoid the collision. If the distance between ships is smaller than this criterion, collision is then likely to happen.

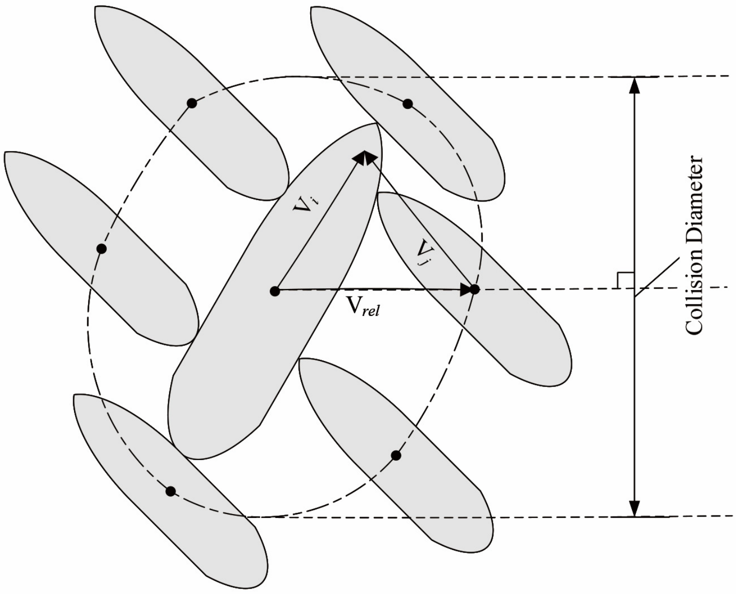

Figure 2.3 Collision diameter (Fujii and Shiobara, 1971)

Fujii and Shiobara (Fujii and Shiobara, 1971) indicated that CD is proportional to the lengths of ships; however, the explicit mathematical method to obtain such parameter is not provided. This work is fulfilled by Pedersen (Pedersen, 1995), as shown in Eq.2.3:

$$D_{\text{ij}} = \frac{\left(L_i V_j + L_j V_i\right)}{V_{ij}} \sin\theta + B_j \left\{1 - \left(\sin\theta \frac{V_i}{V_{ij}}\right)^2\right\}^{\frac{1}{2}} + B_i \left\{1 - \left(\sin\theta \frac{V_j}{V_{ij}}\right)^2\right\}^{\frac{1}{2}} \tag{2.3}$$

where:

L_i, L_j - Length of the ship i and j;

B_i, B_j - The width of the ship i and j;

V_i, V_j - The speed of ship i and j;

V_{ij} - Relative speed;

θ - Course difference;

Based on this criterion, a series of methods have been developed. One major group is to establish stochastic process models to estimate geometric collision probability. The idea is to build probability function of collision candidates based on CD, by taking traffic flow information (average dimensions, speed, course for a certain category of the ship, etc.) into consideration, to estimate the probability of two ships which violate such threshold. The most representative model for this approach is Pedersen model (Pedersen, 1995), which is shown in figure 2.4.

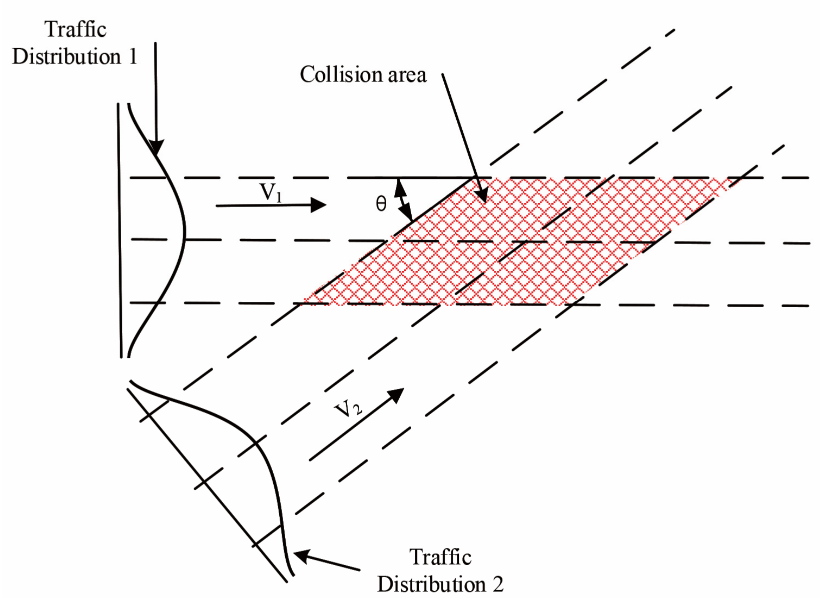

Figure 2.4 Illustration of Pedersen's model (Pedersen, 1995)

Suppose two waterways intersect as figure 2.4 indicates, the traffic flows within them follow certain normal distributions. The geometric collision probability within the risk area can be obtained according to Eq. 2.4:

$$N_a = \sum_i \sum_j \iint_{\Omega(z_i z_j)} \frac{Q_{1i} Q_{2j}}{V_i^1 V_j^2} f_i^{(1)}(z_i) f_j^{(2)}(z_j) V_{ij} D_{ij} dA \Delta t \tag{2.4}$$

where:

Q_{1i} Q_{2j} are traffic volume of ship category i and j in waterway 1 and 2, respectively;

V is the average speed of each category of the ship;

$f_i^{(1)}(z_i)$ is the traffic distribution of each category of the ship;

V_{ij} is relative speed;

D_{ij} is collision diameter;

Similar works can also be found in (COWI, 2008), etc. Utilising this criterion, various applications have been conducted: Kujala et al. (Kujala et al., 2009) conducted research on maritime traffic safety in the Gulf of Finland, within which Pedersen model was introduced to obtain geometric collision probability. Silveria et al. (Silveira et al., 2014; Silveira et al., 2013) analysed traffic patterns in the coast of Portugal using AIS data, based on which probability of collision within these waterways is obtained in the same manner. A similar approach was also adopted by Christian and Kang (Christian and Kang, 2017) to estimate the probability of collision of the ship which transports spent nuclear fuel and Cucinotta et al. (Cucinotta et al., 2017) to obtain the frequency of ship-ship collision in Messina Strait. Dong and Frangopol (Dong and Frangopol, 2015) utilised a similar method to estimate the probability of ship-ship collision as part of collision risk analysis considering multiple risk attitudes.

Compared with synthetic indicator approach to obtain the geometric collision probability, researches utilising collision diameter focus more on the current status of traffic flow rather than analysing the linear projected status between ships. By doing this, the potential error of detection due to the linear assumption could be avoided. Another advantage of such an approach is the conciseness and simplicity of application, where most of the work focuses on establishing the stochastic process models. One can find this approach has already been implemented into risk analysis software such as GRounding And Collision Analysis Toolbox GRACAT (Friis-Hansen and Simonsen, 2002) and International Association of Lighthouse Authorities Waterways Risk Assessment Program (IWRAP) (IALA, 2009), etc. However, as collision diameter is established upon the assumption that two ships have almost physical contact, some scholars also argue that it could lead to a potential underestimation of the results (Montewka et al., 2010).

Ship Domain

Ship domain, which was proposed by Fujii and Tanaka (Fujii and Tanaka, 1971) is another important concept utilised in risk analysis of ship-ship collision accident. According to the definition, the ship domain indicates a space around the ship that would like to be kept clear from others. The intrusion or overlap of such area between ships can indicate the potential for collision. The graphical illustration of ship domain is shown in figure 2.5. For details about ship domain, and interested readers can refer to the literature review by Szlapczynski and Szlapczynska (Szlapczynski and Szlapczynska, 2017b) for more information.

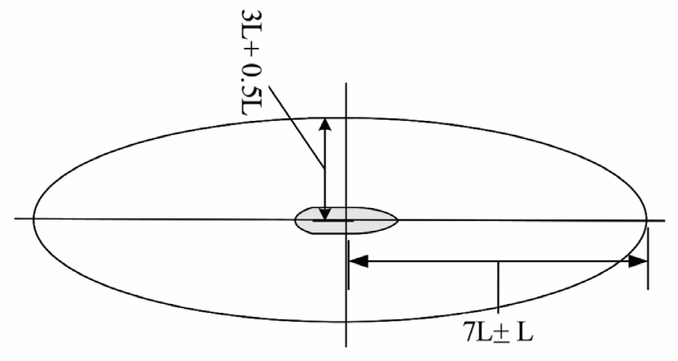

Figure 2.5 Illustration of ship domain

The principle for collision risk analysis using ship domain is that if the domain was violated by other ships or overlapped by other domains, collision accident is then likely to happen due to potential misconduct of ship behaviour or influence of external factors (wind, current, etc.), etc. It provides another angle to measure spatial proximity between ships. However, it also focuses on the current spatiotemporal relationships between ships.

Under such logic, various approaches have been proposed in literature from individual ships and macroscopic perspective, respectively, among which model-based data analysis and computer simulation are two major technical approaches. For model-based data analysis, ship domain is utilised as the criteria for collision candidate detection where historical traffic data, such as AIS data, etc. are introduced to obtain the probability or frequency of domain violation/overlap. Such logic is also implemented in a computer simulation, while the difference is that historical traffic data are analysed to obtain traffic characteristics as simulation input rather than being directly utilised as data sources. Literature which applied ship domain as criteria is illustrated in table 2.4, followed by detail descriptions:

Table 2.4 Sources of literature for ship domain approaches

Technical approach	Sources
Model-based data analysis	(Chai et al., 2017; Montewka et al., 2012; Montewka et al., 2010; Qu et al., 2011; Wang, 2010; Weng and Xue, 2015)
Computer simulation	(Goerlandt and Kujala, 2011; Goerlandt et al., 2012; Rong et al., 2015)

Wang et al. (Wang, 2010; Wang et al., 2009) provided a concise mathematical expression to describe different shapes of ship domain which is named as quaternion ship domain, and it can be adapted in various application scenarios and various navigational rules, e.g. COLREGs. Their quaternion ship domain facilitates the utility of ship domain in many aspects, especially in collision risk assessment. For instance, Qu et al. (Qu et al., 2011) conducted a risk assessment for collision accident in Singapore strait where the overlapping of Fuzzy Quaternion Ship Domain (FQSD) is implemented as one of the indicators to reflect risk level. Different from Wang's work, Montewka et al. (Montewka et al., 2012; Montewka et al., 2010) proposed a new form of ship domain by considering ship manoeuvrability and applied such model into collision probability estimation. Baldauf et al. (Baldauf et al., 2015) proposed manoeuvring areas, which is an area around the ship, and was originated from research in aviation, into risk analysis and collision avoidance research by considering ship manoeuvrability.

As for the application of ship domain in collision candidate detection, Weng and Xue (Weng and Xue, 2015) estimated collision frequency in Singapore fairways using the violation of circularly shaped ship domain as criteria, which was further developed and introduced in Chai et al.'s research (Chai et al., 2017). Besides this, Goerlandt et al. (Goerlandt and Kujala, 2011; Goerlandt et al., 2012) established maritime traffic simulation models to estimate the probability of collision where ship domain is utilised as the criterion for dangerous encounters. Instead of utilising intrusion of ship domain as criteria of dangerous encounter, Szlapczynski, et al. (Szlapczynski and Szlapczynska, 2016) proposed a new model to analyse the risk of collision by introducing two indices: the Degree to Domain Violation (DDV) and Time to Domain Violation (TDV) to replace DCPA and TCPA by using ship domain.

Compared with collision diameter, ship domain also assesses the potential of a collision via violation/overlapping based on the analysing maritime traffic information, e.g. AIS data or by computer simulation, etc. However, in practices, several issues have influences on the models' reliability: 1) Choice of ship domain. As indicated, various forms and shapes of ship domain are proposed in the literature, taking different factors, e.g. ship manoeuvrability, local traffic characteristics, etc. into account. And 2) Potential over/underestimation. For geometric probability estimation based on ship domain, many works are conducted by analysing data with a certain time interval. Such approaches could lead to a situation where the dangerous encounter between the interval is not detected.

Velocity-based Approach

For traditional research, the geometric collision probability is determined and measured, utilising spatiotemporal relationships between ships. However, the methods mentioned above consider spatiotemporal relationships separately by introducing various elements, e.g. TCPA, DCPA, TDV, DDV, etc. Under such situation, conflicting indications may arise, e.g. for certain encounter situation, the DCPA can be very small while TCPA could be very large.

The velocity-based approach provides another perspective for collision risk analysis. The idea was addressed in work by Degre and Lefevre (Degre and Lefevre, 1981), as shown in figure 2.6, where the distance, velocities between ship A and B are presented in velocity space of ship A (own ship), and the shadow area is the possible velocities for ship A that the collision is likely to happen if it takes them. Lenart (Lenart, 1983, 2015) formulated this idea as Collision Threat Parameter Area (CTPA) by assuming the ships keep their speed and headings constant during navigation. A CTPA is illustrated in figure 2.7. Later on, many researchers follow this idea and expand it in maritime practice.

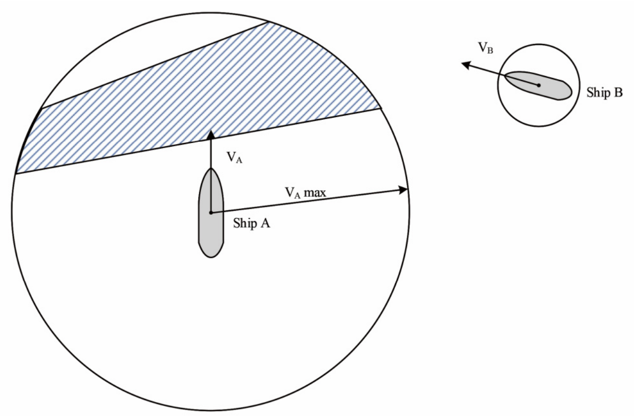

Figure 2.6 Illustration of room to manoeuvre

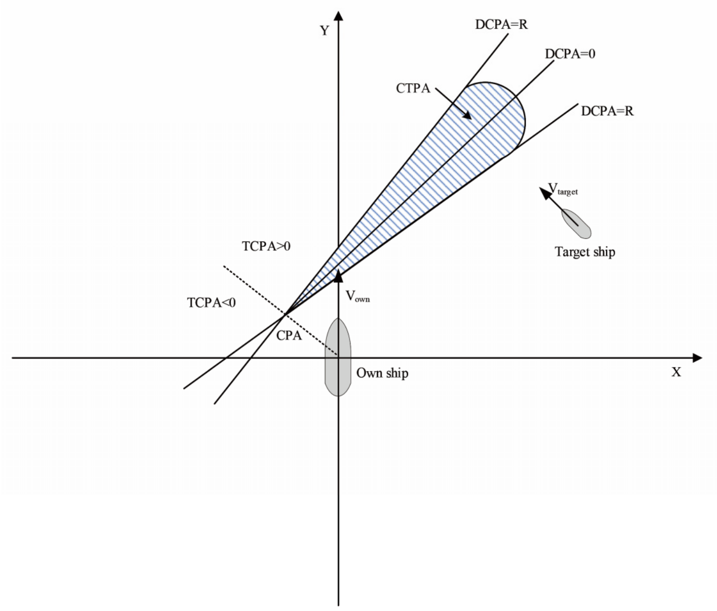

Figure 2.7 Illustration of CTPA

This idea is also well-studied in the robotics domain, where this method is called the Velocity Obstacle (VO) algorithm. Researchers loosened the linear motion assumption from linear to nonlinear and from deterministic to probabilistic. Maritime researchers also notice these developments. Huang et al. (Huang and van Gelder, 2017; Huang et al., 2018) proved that CTPA is identical to linear VO and they are another form of T/DCPA in velocity space. Additionally, the author also demonstrates the non-linear VO, Probabilistic VO, and Generalized VO algorithms(Huang et al., 2019b) in the maritime environment. The non-linear

Velocity obstacle is shown in figure 2.8. For interested readers about the application of the velocity obstacle algorithm and its improvements in collision avoidance research, please refer to (Huang and van Gelder, 2017; Huang et al., 2019b; Huang et al., 2018).

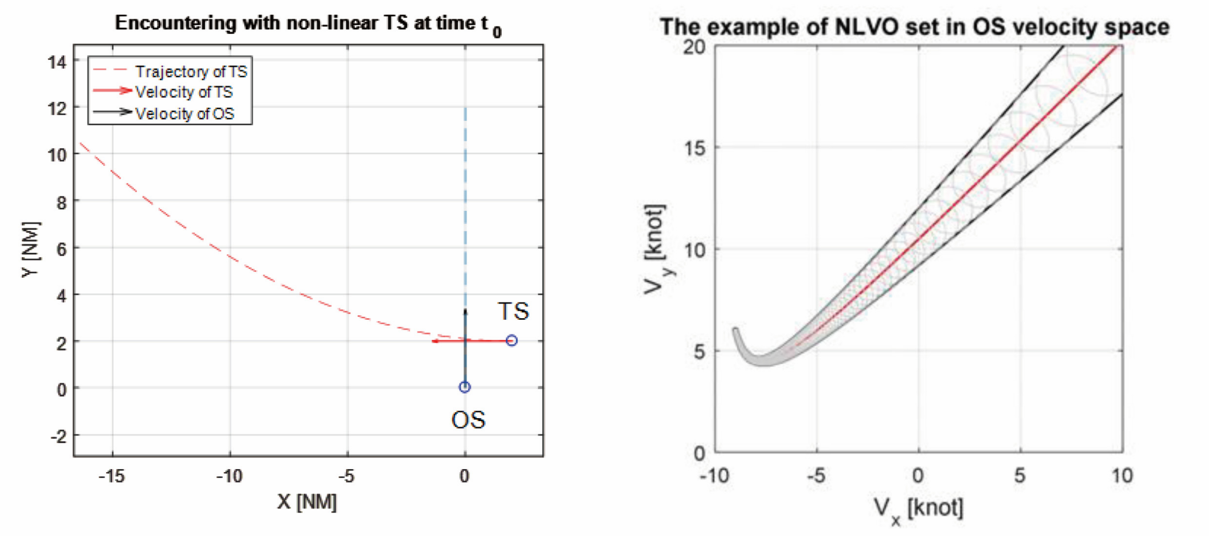

Figure 2.8 Non-linear Velocity Obstacle (Huang and van Gelder, 2017)

For the velocity-based approach in collision probability research, few works have been conducted since it is a relatively new idea in the maritime domain. Many focused on identifying collision risk from the individual perspective, e.g. Huang et al. (Huang et al., 2016) utilised VO set to measure the collision risk which is formulated as the proportion of reachable velocity leading to collision; Zhao et al. (Zhao et al., 2016) developed a collision avoidance algorithm for the unmanned surface vehicle where VO was utilised as a criterion of collision risk. Szlapzynski et al. (Szlapczynski and Krata, 2018; Szlapczynski and Szlapczynska, 2017a) conducted a series of research to further develop CTPA with the combination of ship domain as the replacement of minimum safe boundary in the algorithm.

Several scholars have conducted work on macroscopic risk analysis with the velocity-based approach: Van Westrenen and Ellerbroek (van Westrenen and Ellerbroek, 2017) analysed near miss on the North Sea where the variation of CTPA is utilised as the criterion of near misses (collision candidates). Based on the non-linear VO, the authors (Chen et al., 2018) also developed a collision candidate detection method as an approach for probabilistic risk analysis and compare the method with eight collision candidate detection methods which utilise ship domain and CPA as of the criteria. The results indicate with non-linear VO, the reliability of collision candidate detection is improved to some extent.

Compared with synthetic indicator and safety boundary approaches, one of the major advantages of Velocity-based approach is that it considers spatiotemporal proximity between ships in velocity space, a space that can consider these two dimensions at the same time. It also provides the opportunity to consider the whole procedure of encounter as the basis to detect collision candidates instead of analysing time-sliced data. In this manner, the potential error of the results can be reduced, which in turn, could improve the reliability of results in terms of parameter choices of the models.

2.4.3 Causation Probability

As a variable that describes the possibility that ships in encounter situation result in actual collision accident due to factors such as mechanical failures, human factors, etc., the causation probability is an indispensable element for probabilistic risk analysis of ship-ship collision under Eq. 2.1. In this section, the major approaches for obtaining such probability are collected and elaborated.

1) Statistical Analysis Approach

Analysis based on the historical accident data is one of the fundamental methods to obtain insights into the influence of human and other factors on the probability of ship-ship collision. Information such as accident investigation reports, accident databases, e.g. Marine Casualties and Incidents information from Global Integrated Shipping Information System (GISIS) established by IMO, are often referred to as the data source. To conduct such analysis, statistical analysis methods such as regression, frequency analysis, etc. are introduced. By investigating the historical accident statistics in Japanese waters, Fujii et al. (Fujii and Shiobara, 1971; Fujii et al., 1984) estimated the causation probability in difficult situations, the result of which has been widely adopted in related works, see (Hänninen and Kujala, 2009; Kujala et al., 2009; Pedersen, 1995), etc. Besides the approach that directly estimates causation probability based on historical data, research on identifying contributing factors and their inter-relationships are also conducted, e.g. (Bye and Aalberg, 2018; Zhang et al., 2018b).

With its simplicity and straightforwardness, such analysis has been widely applied in local risk assessment, the results of which have also been applied in many succeeding works, e.g. (Friis-Hansen and Simonsen, 2002; Kujala et al., 2009; Montewka et al., 2014), etc. However, as the ship-ship collision is a category of the accident with the rare occurrence, the amount of accident investigation reports may not be sufficient to conduct the analysis; meanwhile, the quality of the data (e.g. incomplete information) also diminishes the efficacy of the results. Therefore, new methods that could integrate extra information, e.g. expert knowledge are introduced.

2) Fault Tree Approach

As aforementioned, a large proportion of collision accidents are caused by human and organisational factors and their inter-relationships (Ren et al., 2008). To obtain the probability of collision caused by these factors, analytical methods are necessary to be implemented. Fault Tree Analysis (FTA), which is developed to perform deductive analysis of system failure based on Boolean logic, is one of the classic approaches for this task.

FTA is generally conducted based on causation analysis of either accident investigation reports, or knowledge from experts in the field, based on the relevant literature. Accident contributing factors, e.g. negligence of watchkeeping, fatigue, engine failure, etc. are identified as "Event" in the model, together with their causation relationships. Research on Human reliability analysis have facilitated such process from various aspects, e.g. determine, classify the contributing factors, and their causal relationships, etc. (e.g. (Harrald et al., 1998; Martins and Maturana, 2013; Xi et al., 2017)). These "Events" are grouped into various parts based on the causation relationships identified in the form of Boolean gates, e.g. "AND", "OR", etc. and finally synthesised into the tree-shaped structure to graphically illustrates the effects of components to the top event (ship-ship collision). The occurrence probability of each component was obtained based on statistically analysis, interview, questionnaire, etc. and the probability of ship-ship collision accident (top event) can be calculated using Boolean algebra.

In practices, FTA is usually utilised to obtain the causation probability of ship-ship collision and analyse the corresponding causes. Such an approach is also advised by the IMO as one of the suggested approaches to perform Formal Safety Assessment (FSA) for the maritime accident (IMO, 2018a). When Pedersen (Pedersen, 1995) proposed the mathematical model for collision candidates estimation, causation probability in his model was also calculated by a concise FTA. Following the guideline of FSA, Martins and Maturana (Martins and Maturana, 2010) analysed the contribution of human errors to ship-ship collision accident and built a comprehensive Fault Tree to estimate causation collision probability. Similar research was also conducted by Ugurlu et al. (Uğurlu et al., 2013) where the probability of collision accident was estimated considering multiple factors.

Compared with the statistical analysis approach to obtain the causation probability of ship collision, FTA integrates causal analysis, which identifies the accident causations and their inter-relationships, and historical accident data. During the procedure, knowledge from field experts can be introduced to determine the structure of the factors. According to the literature, FTA has obtained popularity in causation probability analysis since its concise structure and simplicity to implement, however, due to the nature of the binary state of variables in the model, it could be difficult to define some factors which contain multiple possible states.

3) Bayesian Approach

Although FTA has been introduced into a risk analysis of ship-ship collision accident, some characteristics of itself have constrained its applicability in this field. One of them is its exponentially growing structure, which was already identified by Li et al. (Li et al., 2012). The structure of Fault tree will become complicated to a large extent when multiple factors are considered. Another characteristic is that due to the nature of FTA is based on Boolean logic, the state of each component is binary, which is not suitable for factors with multiple states. To improve such deficiencies in FTA and further develop methods for collision risk analysis which can model multi-state and non-linear causation relationships between accident contributing factors, the Bayesian approach has been introduced into research and drew much attention from the academia.

Bayesian network is a graphical inference network based on Bayesian theorem. Three elements composed Bayesian network: directed acyclic arc, which demonstrates causation relationships between accident contributing factors; node, which indicates accident contributing factors, and Conditional Probability Table (CPT), which contains conditional probabilities of each state of the variables. For the details of the Bayesian network, interested readers may refer to (Langseth and Portinale, 2007). Compared with FTA, the Bayesian network allows factors to have multiple states and the probabilities of each state under different conditions are given by CPT of each node. The joint probability of the network can be obtained according to Eq. 2.5:

$$P\left(X_1 = x_1, X_2 = x_2, \cdots, X_n = x_n\right) = \prod_{t=1}^{n} P\left(X_1 = x_1 \middle| X_{pa(t)}\right) \tag{2.5}$$

where: X_n are the contributing factors considered in the network and x_n is the corresponding given state. A simple example of the Bayesian network model is illustrated in figure 2.9:

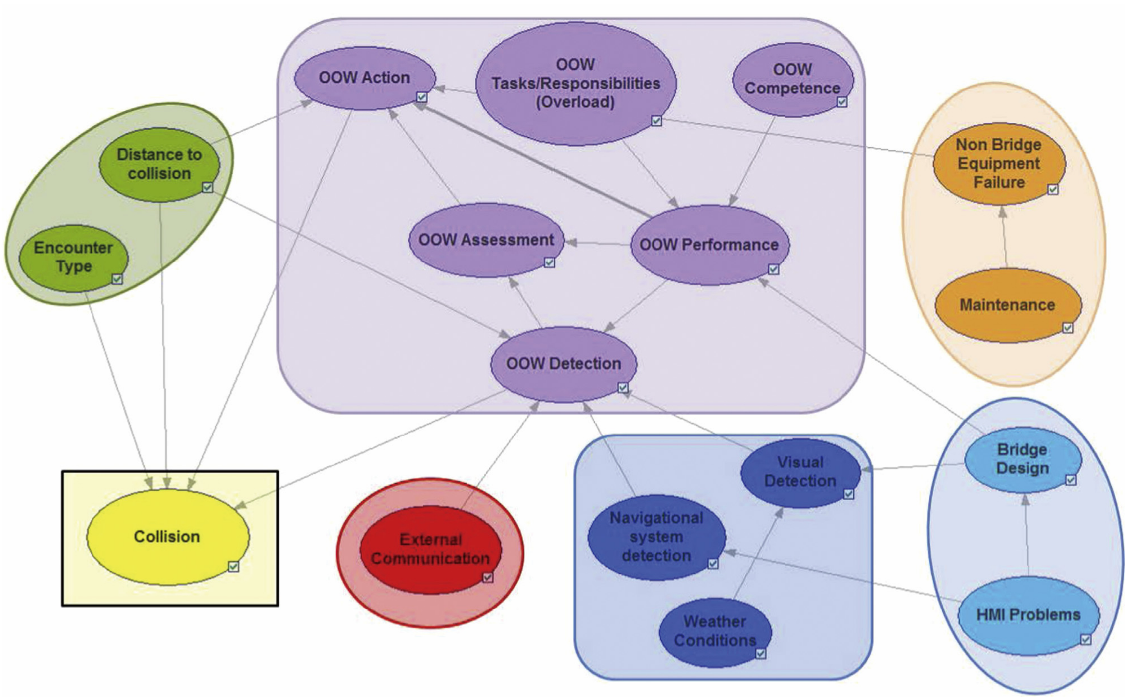

Figure 2.9 Generic Bayesian Network of collision risk modelling (Sotiralis et al., 2016)

When applying this method to estimate the causation probability of ship-ship collision accident, several elements need to be clarified. Langseth and Portinale (Langseth and Portinale, 2007) have pointed out that: "*Decide what to model; Defining variables; Build the qualitative part; Build the quantitative part; Verification*" is the phases necessary to build the Bayesian network model, which have been applied by Montewka et al. (Montewka et al., 2014) as a framework for risk analysis of collision accident of RoPax vessel. Also, the process of obtaining the accident contributing factors and their causal relationships are benefited from research on HRA. Many HRA methods, e.g. CREAM, HFACS, etc. are incorporated with Bayesian network to analyse, determine the human and organisational factors and their causal relationships in a comprehensive and structured manner, e.g. Martins and Maturana (Martins and Maturana, 2013) incorporated HRA analysis and Bayesian network to analyse the probability of ship-ship collision accident. Graziano et al. (Graziano et al., 2016) proposed a classification system for human errors in ship grounding and accident using Technique for the Retrospective and Predictive Analysis of Cognitive Errors (TRACEr), which can facilitate the establishment of the Bayesian network for causation probability modelling.

With its openness and flexibility in incorporating multiple sources of information, e.g. Expert knowledge, stochastic simulation results, historical data, etc. The Bayesian network has become a popular model under this method. Trucco et al. (Trucco et al., 2008) establish a probabilistic model to analyse the risk of human and organisational factors in the ship-ship collision, where the Bayesian network is utilised as to obtain their probabilistic correlations and probability of the accident. Similar researches have also been done by Martins and Maturana (Martins and Maturana, 2013), and Sotiralis et al. (Sotiralis et al., 2016). Montewka et al. (Montewka et al., 2014) established a framework for risk analysis of collision involving Ropax ship with the Bayesian network, where multiple sources of information, including simulation results, expert knowledge, etc. are included to obtain the probability of collision with certain consequence. Apart from obtaining the probability of collision accident, the Bayesian network can also be utilised to determine the influence of contributing factors to the accident because of its characteristic of two-way inference. Sensitivity analysis of the method to achieve that. (Hanninen and Kujala, 2012) conducted research on identifying the influence of the contributing factors to collision accident and proposed three methods to implement.

Apart from the advantages of utilising the Bayesian network to model causation probability and analysing their inter-relationships, when in the practices, there are several issues concerning Bayesian network. Hanninen (Hanninen, 2014) and Zhang and Thai (Zhang and Thai, 2016) have conducted a review on this method in regards to its benefits, challenges, and procedures of expert knowledge elicitation, where scarceness of accident data, the complicated dependency and causation relationship between contributing factors and uncertainty among the models are considered complicate for model construction. To alleviate the influence of incomplete data when building the Bayesian network, Zhang et al (Zhang et al., 2018a) introduced Credal Network, which is an extension of Bayesian network by Antonucci et al (Antonucci et al., 2010; Antonucci and Zaffalon, 2008) to conduct probabilistic inference of Bayesian network with uncertainty. In this manner, the probability of collision will be obtained in the form of interval instead of point estimates. Besides, expert knowledge is still an indispensable source of information when identifying the factors and their probability. How to elicit the knowledge from expert properly and diminish bias will be one of the critical problems.

2.5 Discussions

2.5.1 Relations of Collision Risk Analysis Methods for Individual Ships and Macroscopic Risk Analysis

Analysing and estimating collision candidates is one of the critical elements for probabilistic collision risk analysis. The number of collision candidates, its spatiotemporal characteristics, etc. can provide constructive insights to stakeholders such as maritime safety authorities to understand the current risk situation and facilitate them to propose corresponding risk mitigation measures.

The critical element for geometric collision probability is how to define and identify collision candidates or near misses, i.e. to adopt what criteria to determine which encounter is dangerous. To do this, variables such as DCPA and TCPA, Collision Diameter, MDTC (Minimum Distance To Collision)(Montewka et al., 2010), Ship Domain, Velocity Obstacle, etc. are introduced as the basis to construct various approaches of candidate detection by measuring the proximity between ships in spatiotemporal domain. The knowledge and experience from individual collision risk analysis have facilitated the development of the topic in a macroscopic perspective to a large extent. Such finding is based on three facts: 1) The strong similarities between these criteria and collision risk detection method for individual ships; 2) Determination of collision candidates is usually conducted between two ships, where multiple-ship encounters will be decomposed into multiple two-ship encounter scenarios; and 3) The results of collision candidate detection are usually the summation of the identified dangerous ship pairs. In the meantime, the results of macroscopic risk analysis can also facilitate risk analysis and prevention for the individual ship. The risk mitigation measures based on spatiotemporal characteristics of collision candidates in certain waterways could act as background knowledge for OOWs onboard. Besides, as Mou et al. (Mou et al., 2010) argued, for research utilizing CPA parameters, prioritising collision avoidance for multiple targets could be improved.

However, in practices, current approaches to obtain the number of collision candidates as geometric collision probability and its characteristics usually analyse pair of ships in encounter situations. During such process, encounters, where more than two ships involved, will be intentionally divided into multiple sub-situations, which could lead to potential overestimate of results. To obtain results which could better reflect safety level in waterways, approaches that can consider multiple encounters should be improved.

2.5.2 Comparison Among Collision Candidate Detection Methods

Among the literature, model-based data analysis, stochastic process model, and computer simulations, etc. can be frequently found to estimate the geometric probability for the ship-ship collision. Combined with additional information, e.g. causation probability, etc. collision risk and its insights can be obtained for certain waterways. Although the implementations are different from one another, the common element for them is that it is critical to adopt certain criteria to determine dangerous encounters, i.e. collision candidates.

Proximity is the key element to perform the task, either in spatial, temporal domain or both, which can be considered introduced from individual ship perspective. The traditional synthetic indicators criteria, e.g. CPA-based approaches are to measure spatial and temporal proximity between ships using DCPA and TCPA, distance, speeds, etc., respectively, under the assumption that both ships will maintain their kinematic status throughout the whole process. However, since some models provide separate estimations on the parameters, in certain situation it could give contradictory results, e.g. small DCPA value but large TCPA value, which make the determination of collision candidate difficult. Some scholars have proposed criteria combining DCPA, TCPA using the linear/non-linear equation to improve it to some extent. As for safety boundary-based criteria, they are utilised to estimate spatial proximity at a certain time interval for the data-driven mathematical model, stochastic model, and computer simulation approaches.

Among the various approaches for geometric collision probability, the reliability of them is questioned by some scholars. Goerlandt and Montewka (Goerlandt and Kujala, 2014) have conducted a comprehensive analysis of the reliability of collision candidate detection methods. The results indicate a significant difference due to the different criteria introduced and methods parameter settings. As for the inter-methodological difference of the results, such difference is reasonable since different criteria are introduced for the task.

In general, when in comparison, the issues of these approaches focus on two aspects: 1) Low inter-methodological reliability; and 2) High influence of parameter choices for the adopted method. Involvement of time interval for collision candidate detection can be one of the reasons. During the encounter process, the value of indices which are utilised as criteria can fluctuate due to the interactions between ships. Such fluctuation, combined with the involvement of the time interval, could lead to over/underestimation of the results. For inter-methodological reliability issue, it is very challenging to propose which one is accurate due to the lack of standard labelled datasets for benchmarking. However, the reliability of results in terms of parameter settings, when in the application, can be improved by considering the whole process of the encounter as proposed in (Chen et al., 2018), rather than analysing traffic data with an interval of time.

2.5.3 Human and Organisational Factors in Collision Risk Analysis

The maritime transportation system is a complex system where human and organisational factors are highly involved. The behaviours of ships are governed by the officers on board, based on regulations, their perceptions, and experiences. During the process of decision making and execution, failure of human reliability, errors from human and organisational aspects could contribute to the occurrence of collision accident to a large extent.

For research on causation probability of collision accident, three major approaches can be identified from the literature: 1) Probabilistic analysis, which aims at obtaining collision probability caused by human and operational errors; 2) Accident contributing factors analysis, which is to identify the contributing factors of ship-ship collision, to analyse their causal relationships and to determine major factors that can be utilised for risk reduction; and 3) Human reliability analysis, which is to systematically identify and analyse the cause and consequences of human errors (Groth and Swiler, 2013). These approaches are closely intertwined with each other as the goals of such analyses in probabilistic risk analysis of ship-ship collision are to find the mechanism of human and organisational factors that caused a collision, to quantify such probability and propose risk mitigation measures with respects to the factors.

Statistical analysis of historical collision accident is one of the fundamental techniques for the approaches aforementioned, e.g. (Bye and Aalberg, 2018; Graziano et al., 2016; Zhang et al., 2018b), etc. Accident investigation reports contain detailed information about the process of the accident, and the identified causes for the accident by the investigation authority, e.g. loss of watchkeeping, mechanical failure, etc. Such information can be utilised directly to identify the influence of human and organisational factors on the collision, but also be processed to estimate collision risk in the forms of probability. Besides, research on accident mechanism and decision-making procedure, etc. have been widely applied in this field. FTA and Bayesian network, etc. are introduced to analyse the structure of system failure and the causation relationships between accident contributing factors, to obtain the causation probability and identify significant factors for risk mitigation. During the process of FTA and Bayesian network modelling, works from HRA research have facilitated them by providing guidelines for factors and causation relationships determination (e.g. (Martins and Maturana, 2013)), classification (e.g. (Yıldırım et al., 2019)), and expert elicitation (e.g. (Harrald et al., 1998)).

When applying such methods to get insights about human and organisational risk of collision, due to the scarce nature of collision accident, it is difficult to perform data-driven approaches; therefore, additional information, e.g. expert knowledge is important to be included, especially for determining the causal relationship between the contributing factors and establishing the structures of Fault/Event tree and Bayesian network. However, during the procedure, the uncertainty and elicitation process is often discussed (Zhang and Thai, 2016). To improve the reliability of causation probability, methods that deals with uncertainty and expert knowledge elicitation process should be improved and integrated into the process. For example, Zhang et al. (Zhang et al., 2018a) introduced "Credal Network (Antonucci et al., 2010; Antonucci and Zaffalon, 2008)" to conduct probabilistic inference with the interval to consider epistemic uncertainty in the causation probability model.

2.5.4 The Model Choice for Different Stakeholders

For different stakeholders in the maritime traffic system, due to their various and different interest of concerns, which have been analysed in section 2.3, the applicability of the methods mentioned in the previous sections for them are different. Therefore, it is necessary to discuss which methods can be utilised for different stakeholders.

For maritime safety authorities, their interests of concerns are concluded as follows: 1) Frequency of accident or near-miss occurrence, which is important KPI to evaluate the performance of maritime authorities (Mou et al., 2019; Valdez Banda et al., 2016b); 2) Potential consequence of accident, e.g. oil spill, etc.; and 3) Human and organisational factors. All the interests concern different components of the risk analysis of ship-ship collision accident. For frequency problem, the statistics-based approach (e.g. (Kujala et al., 2009; Yip, 2008), etc.) is one of the fundamental approaches that can be utilised. Besides, methods utilised to obtain geometric and causation probability, e.g. synthetic indicator, and safe boundary approach, etc. are now the mainstream of research for obtaining the frequency of accident. For the potential consequence estimation, probabilistic approach such as Bayesian network is an effective tool to estimate the consequence of ship-ship collision accidents (e.g.(Goerlandt and Montewka, 2015a)). However, since the details on accident consequence research are out of the scope of this chapter, methods for this type of interests is not included. For human and organisational factors, methods for HRA, e.g. CREAM, HFACS, etc. can be utilised as guidelines to identify accident contributing factors from multiple sources of information, and act as a taxonomy to facilitate the determination of causal relationships among the factors. To probabilistically quantify the influence of them on the occurrence of ship-ship collision accidents, Bayesian network, FTA etc. can be incorporated.

For individual ships, risk detection and resolution are the main interests of concern of collision risk during navigation, e.g. to detect the risk of collision and perform proper collision avoidance manoeuvre. From this perspective, approaches illustrated in section 2.4.1 can be incorporated into risk detection process, e.g. CPA-based approach (Wang et al., 2017), ship domain approach (Szlapczynski and Szlapczynska, 2017a), and velocity-based approach (Huang et al., 2019b; Huang et al., 2018), etc. As for risk resolution, since it is out of the scope of this chapter, the approaches for this is not included.

For ship designers, design, operation, and regulation are three major interests of concern. Ship design is of great importance for safe navigation, crashworthiness and human performance. However, since the research on ship design is out of the scope of this chapter, for interested readers, please refer to literature such as (Deeb et al., 2017; Liu et al., 2018). For ship operation, it concerns how to improve human performance during navigation and encounters, hence, to improve safety and avoid the occurrence of the accident. Methods for HRA, e.g. CREAM, HFACS, etc. can be incorporated to facilitate the process. Besides, the Bayesian network and FTA are effective tools to analyse the influence of ship design factors on human performance, e.g. (Montewka et al., 2017). For risk-based regulations, since it concerns multiple aspects of the system, e.g. traffic management, ship operation, etc., it requires many approaches from different aspects to facilitate the regulation formation process. Therefore, all the approaches mentioned in the chapter can be incorporated with risk-based regulations, depending on its goals and scope.

2.6 Conclusions

In this chapter, a systematic review and analysis of quantitative risk analysis on ship-ship collision accident are presented with the focus on macroscopic perspective for maritime safety management. Major stakeholders and their preferences in risk analysis have been analysed, as well as the risk analysis methods under the framework proposed by Fujii and Shiobara (Fujii and Shiobara, 1971) and Macduff (Macduff, 1974) to provide an overview on the topic.

A classification and introduction of probabilistic risk analysis methods for ship-ship collision have been provided. Detailed analysis of research methods is conducted for the elements of the probabilistic risk analysis framework: geometric and causation probability. For geometric probability, research is classified into the synthetic indicator, safe boundary, and velocity-based approaches, respectively, according to different criteria utilised when determining encounters that have the potential for collision. For causation probability analysis, statistical analysis, Fault tree analysis, and Bayesian network models are chosen as major categories of approaches.

A discussion is presented, and the main findings are as follows: 1) Research on collision risk analysis from individual ship perspective, especially criteria to evaluate ship encounters, have facilitated the research in macroscopic perspective, and in turn, results from macroscopic research can also facilitate individual risk analysis by providing regional risk characteristics, etc. However, among the literature, the geometric probability is usually obtained by evaluating simple encounters where only two ships are involved. To improve the accuracy of the results, methods that can consider multiple-ship-encounter scenarios should be developed; 2) Although different criteria are utilised to propose various approaches, proximity in the spatiotemporal domain is the common element to determine the geometric probability for the collision. However, current approaches usually estimate geometric probability by analysing data at certain intervals, which could lead to over/underestimation of the results. To improve related research, methods that can consider the whole process of encounters should be proposed; 3) For causation probability induced by human and organisational factors in a collision accident, lack of data and uncertainty is a problem to obtain accurate and reliable estimation. To obtain reliable results, methods which could conduct probability inference considering uncertainty should be further developed. 4) For each stakeholder and their interests of concern, the possible choices of methods are also suggested.

Risk analysis and management is an important element for the maritime transport system to prevent the occurrence of accidents, related consequences and their influence on the individuals and societies and to improve the efficiency of the maritime traffic operations in the system. The findings of this work and systematically analysed risk analysis approaches for ship-ship collision accident can provide more insights to peer researchers and risk assessors, to better grasp the merits of current research methods, inter- and intra-categorical relationships and technical characteristics of risk analysis methods, as well as the challenges that need further efforts. The relationship between risk analysis for individual ships and macroscopic perspective provides an opportunity to stakeholders such as maritime safety authorities to propose safety mitigation measures concerning both aspects. The comparison among collision candidate detection methods offers the new understandings to researchers of current methods and their advantages and disadvantages when applied. The analysis of human and organisational factors in collision risk analysis concludes the challenges in practices. Based on these findings, we hope that this work can act as a reference for future research.

Chapter 3 Geometric Collision Probability

As one of the critical elements for ship collision risk modelling, the research on geometric collision probability, also known as collision candidate identification, have drawn much attention from academia. Based on the literature review in chapter 2, we can see that although various methods have been proposed to improve the accuracy and reliability of the results, together with obtaining the insights on the characteristics of the encounters, there are some issues which hinder the development of geometric collision probability modelling: 1) The sensitivity parameter setting in the existing methods, which could lead to potential over/underestimation of the collision candidates; 2) Negligence the perspective that encounter is a process rather than the situation at certain time instance. To overcome the identified problems, this chapter aims at proposing a new perspective to identify collision candidates and estimate geometric probability from the process of encounter, with utilization of Velocity Obstacle (VO) algorithm to improve the resilience of the results with regards to the parameter settings.

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Chen, P., Huang, Y., Mou, J., & van Gelder, P. H. A. J. M. (2018). Ship collision candidate detection method: A velocity obstacle approach. *Ocean Engineering*, 170, 186-198.

Chen, P., Huang, Y., Papadimitriou, E., Mou, J., & van Gelder, P. H. A. J. M. (2020). An Improved Time Discretized Non-linear Velocity Obstacle Method for Multi-ship Encounter Detection. *Ocean Engineering*, 196: 106718.

3.1 Introduction

Encounter is a type of situation that frequently occurs between ships in the waters. One of the critical task for navigators is to safely pass the target ships following the corresponding navigation regulations, e.g. COLREGs. However, due to some unexpected factors, the encounter may develop into a certain situation where it has the potential for an actual collision accident. Following the framework proposed by Fujii (Fujii and Tanaka, 1971) and Macduff (Macduff, 1974), detection and estimation of the number of collision candidates is the first step to perform quantitative collision risk analysis. The results of candidate estimation can be an indicator that reflects the navigational safety level of certain waterways. Combined with information, e.g. maritime traffic information, historical accident, etc., the characteristics of the collision candidates and their correlations between the extra information can be exploited to facilitate maritime safety authorities to propose risk mitigation measures. To obtain a clear understanding of the risk level in the waterways and manage the safety level, identification of these dangerous encounters is one of the interests of the MSA(Mou et al., 2019).

To obtain collision candidates, many scholars have proposed various methods, e.g. (Chai et al., 2017; Lenart, 1983; Pedersen, 1995; Qu et al., 2011), etc. The essence of these researches is to propose a method that can obtain and analyse the spatiotemporal relationships between ships, i.e. to find the answers to this question: *how can the spatiotemporal relationship between ships be measured and how can it be interpreted dangerous?* From the existing literature as shown in chapter 2, one can find that the research on this topic can be classified into three categories: 1) Synthetic indicator approach, i.e. the spatiotemporal relationships between ships are obtained and measured with certain physical indicators and/or the mathematic combination of them; 2) Safety boundary approach, i.e. an arbitrary designed boundary around ship is introduced as the indicator of risk; and 3) Velocity-based approach, i.e. the spatiotemporal relationships are transformed into the velocity domain to obtain a concise presentation of the encounter situation. In the current research, we can see that the first two categories are the dominant approaches in the literature, one of the reason might be that the indicators utilised in these works are the indicator that the navigators familiar with, e.g. Violation of the threshold of T/DCPA, SD, MDTC, etc. Once the threshold of these indicators is violated, it implies that the spatiotemporal proximity between the ships have the potential for collision in the future, if the own ship keeps its kinematic status unchanged.

The development in the methods for collision candidate detection hence the analysis on geometric collision probability has facilitated the MSA to obtain insights on the characteristic of maritime traffic in the waterways and the distributions of risk to a large extent. However, in practice, there are some issues among these methods: 1) The assumption that ships will maintain their kinematic status constant, i.e. during the analysis to estimate the indicators, the speed, course, etc. of ships are considered unchanged; 2) Negeliance of the fact that encounter between ships is a process where they first approach then depart from each other. For current methods, the collision candidates are analysed based on the relationships between ships at the moment of detection. However, due to the design of the models, there is a possibility that the dangerous encounter could be missed due to the time of detection; and 3) The fluctuation of the parameters. As the encounters develop dynamically, the indicators may fluctuate during the encounter. However, due to the design of current methods, there is a possibility of over/underestimation of the results. Besides, Goerlandt and Kujala (Goerlandt and Kujala, 2014) has conducted a comprehensive analysis of the reliability of collision candidate detection methods with three criteria: "*1) rerun of the method; 2) same method and data, but different analysis team (different choice of model parameters), and 3) same scope and objective, no restrictions on methods and data*". The results of this work indicate significant difference among the methods due to different criteria introduced and parameter settings of each method.

To solve the aforementioned issues in the current researches, this chapter aims at proposing a new geometric collision probability model based on a new perspective that encounter is a process instead of the condition that can be determined based on the information at the instance of analysis. To achieve this objective, Non-Linear Obstacle Algorithm (NLVO) is introduced as the main approach to implementing the perspective. Multiple criteria are also integrated to verify the applicability of the proposed method. As for the inter-methodological difference, it is very challenging to determine which one is the appropriate method, due to the various criteria behind them and the influence of the regional traffic characteristics. However, the difference caused by parameter setting can be improved.

3.2 Proposed Methodology

In this section, the definition of collision candidate for this research, the details of the methods utilised to establish the collision candidate detection model, and the framework of the methodology are presented, respectively.

3.2.1 Definition of Collision Candidate

For quantitative risk analysis of ship collision accident in ports and waterways, detection of collision candidate and estimation is the first step, e.g. (Altan and Otay, 2017; Chai et al., 2017; Christian and Kang, 2017; Cucinotta et al., 2017). Among the existing models, collision candidate is detected by checking whether the Spatio-temporal relationship (e.g. relative position, relative speed, etc.) between ships at certain time instance satisfies the criteria of collision candidate and is often conducted in the manner that complicated encounter situation is decomposed into multiple ship-ship encounters. CPA parameters, collision diameter, ship domain, and coupled formulation of indices (relative position, distance, speed, course and bearing, etc.) are introduced as the criteria. However, since ship encounter is a process of ships movement, during which velocities and other kinematic parameters of ships are constantly changing, one encounter process of collision candidate could be detected for multiple times due to the fluctuation of the variables concerned. Besides, in some methods, data are analysed at a certain time interval, which could also result in over/underestimation of collision candidate. To mitigate such issues, we propose the definition of collision candidate considering encounter as a process:

Definition: Collision candidate is the pair of ships in an **encounter process** where their Spatio-temporal relationships satisfy certain criteria that has the potential for collision.

Under such definition, existing criteria, e.g. intrusion of ship domain, CPA parameters threshold, etc. can also be integrated. However, as aforementioned, during the process, the variables that reflect the encounter situation can fluctuate to some extent, which also could influence the stability of results. To further reduce the possible duplicate detection due to this fluctuation, here we consider Velocity Obstacles (VO) as the criteria, i.e. if the velocity of one ship falls into its own VO sets induced by the other ship during the encounter process, this pair of ships will be deemed as collision candidate.

3.2.2 VO Algorithm

The idea of utilizing velocity to determine collision risk in the maritime field was first proposed by Degre and Lefevre (Degre and Lefevre, 1981). Lenart (Lenart, 1983) formulates Collision Threat Parameter Area (CTPA) with a similar idea to determine collision danger by checking if the velocity of own ship falls into CTPA. In research on collision avoidance of robotics, the concept of VO has also gained popularity, see (Fiorini and Shiller, 1998; Lee et al., 2016; van den Berg et al., 2011). The idea of VO is to project the Spatio-temporal relationship (relative distance, speed, course, etc.) between objects into velocity domain of the own object and determine if the risk of collision exists, by checking if the own velocity falls into the velocity obstacle zone generated by the projection. CTPA has been proved to be identical to the Linear-VO algorithm, a category of VO that assumed the states of objects (velocity, course, heading, etc.) remain unchanged during the process, by the Huang et al. (Huang et al., 2018). Kuwata et al. (Kuwata et al., 2011) integrate COLREGs (Convention on the International Regulations for Preventing Collisions at Sea) and VO to develop a motion planning algorithm for Unmanned Surface Vessels (UAVs). Van Westrenen and Ellerbroek (van Westrenen and Ellerbroek, 2017) conducted research on analysing relationships between traffic complexity and near misses in the north sea, within which a domain-based conflict detection method that is similar to CTPA are proposed to detection collision candidate. Based on the aformentioned works, we consider it plausible to introduce VO on collision candidate detection and geometric collision risk modelling.

According to the theory proposed by (Fiorini and Shiller, 1998), VO method describes a set of velocities (VO sets) that collision between two objects will happen at a certain time in the future if their velocity falls into this set. Suppose that two ships are in the position shown in figure 3.1, the velocity obstacle sets of ship A induced by B is denoted as $VO_{A|B}$. Both of them are represented by a circle with a diameter of their lengths. The velocity obstacle sets of ship A induced by B is denoted as $VO_{A|B}$. To obtain $VO_{A|B}$, the length of ship A is reduced to a point while ship B was expanded into a circular area with Radius $R = \frac{L_A + L_B}{2}$. This area describes all the possible position of ship B around A when a collision happens, which is also termed as "conflict position $(ConfP)$" (Huang et al., 2018) as figure 3.1 indicate:

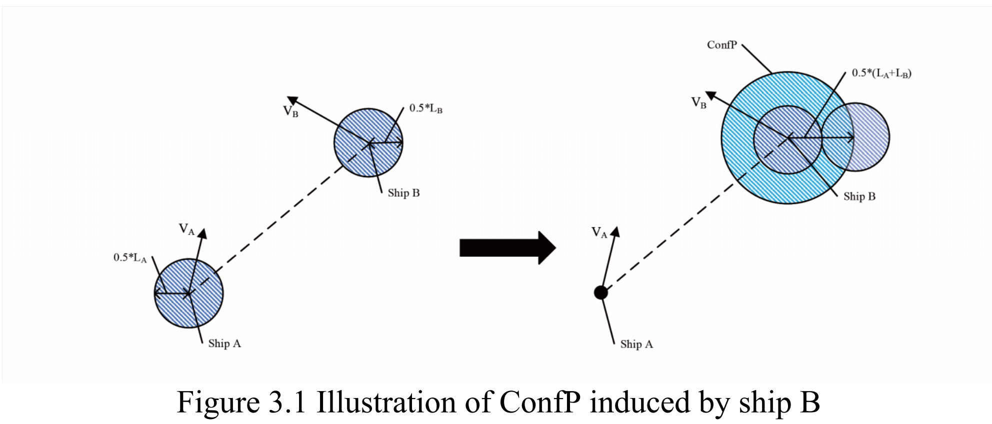


Figure 3.1 Illustration of ConfP induced by ship B

Mathematically, the area "conflict position $(ConfP)$" can be represented according to Eq. 3.1:

$$ConfP = \left\{ \left\| P_A(t) - P_B(t) \right\| \le R \right\} \tag{3.1}$$

Where $\|\bullet\|$ is the Euclidean distance between two ships based their GPS (Global Positional System) coordinates data. If the distance between two ships is less than the radius $R = \frac{L_A + L_B}{2}$, collision is likely to happen. Thus, the condition for a collision happening at time slice t_c can be re-written in Eq. 3.2:

$$P_A(t_C) \in P_B(t_C) \oplus ConfP \tag{3.1}$$

Where $\oplus$ is Minkowski addition which means the elements in $ConfP$ adds with $P_B(t)$.

Based on the definition of criteria, now we suppose two ships $A\{L_A, P_A(t), V_A(t)\}$ and $B\{L_B, P_B(t), V_B(t)\}$ in an encounter situation indicated by figure 3.2 (a). $L, P(t), V(t)$ denotes length, position, and velocity of each ship at time horizon t. Assume that both ships maintain their kinematic statues during the encounter, for a given time t_i after time horizon t_0, condition for the occurrence of collision is that the distance between two ships is no larger than the diameter of $ConfP$, which is mathematically represented in Eq. 3.2. Now substitute P_A and P_B with $P_A = P_A(t_0) + V_A \bullet (t - t_0)$ and $P_B = P_B(t_0) + V_B \bullet (t - t_0)$ according to the assumption, Eq. 3.2 can be rewritten in the form of Eq. 3.3. After this series of transformation, the spatiotemporal criteria for collision is presented in the form related to the velocities of the ships involved in the encounter, which is shown in Eq. 3.3. The graphical interpretation of Eq. 3.3 can be found in figure 3.2(b).

$$V_A \in \left(\frac{d_{BA}(t_0)}{(t - t_0)} + V_B \right) \oplus \frac{ConfP}{(t - t_0)},\ t > t_0 \tag{3.1}$$

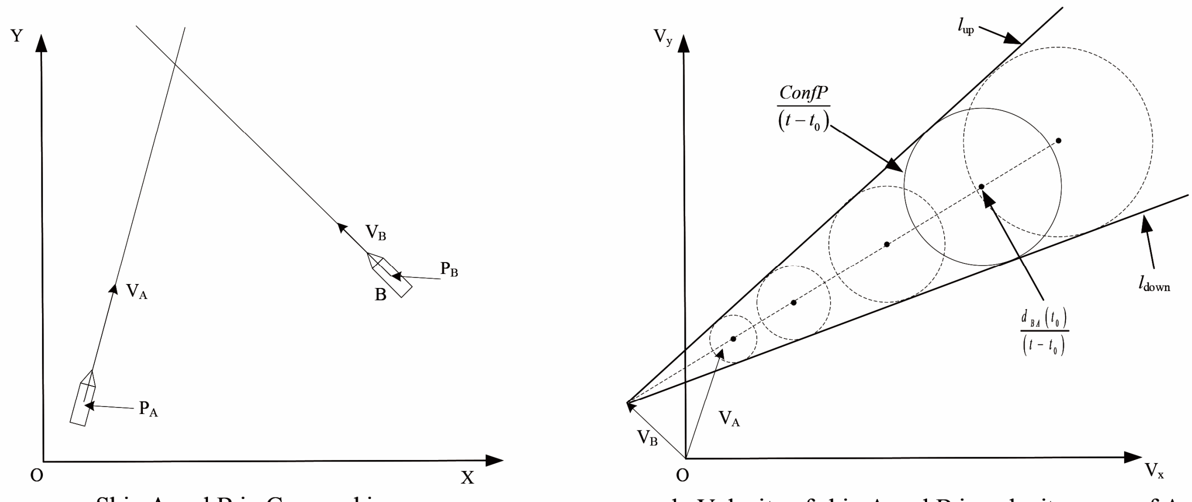


Figure 3.2 Graphical interpretation of VO

From time step t, an infinite number of dangerous velocity sets for ship A at each time in the future of t can be obtained according to Eq. 3.3, which formulate a cone-shaped area with two boundaries l_{up}, l_{down} in the velocity space of ship A as figure 3.2 (b) indicates. For any V_A, the collision will be guaranteed to occur at time t_c after t if and only if V_A falls into this cone-shaped area. Hence VO of ship A induced by B ($VO_{A|B}$) can be defined as Eq. 3.4:

$$VO_{A|B} = \bigcup_{t}^{\infty} \left(\frac{d_{BA}(t_0)}{(t-t_0)} + V_B \right) \oplus \frac{ConfP}{(t-t_0)} \tag{3.1}$$

Due to the assumption that both ships maintain their kinematic status unchanged during the whole process, this category of VO method is defined as Linear Velocity Obstacle (LVO).

3.2.3 Non-Linear Velocity Obstacle (NLVO) Algorithm

In LVO, there is one strong assumption that both ships maintain their kinematic status unchanged during the whole encounter process. However, in reality, such an assumption is rarely satisfied due to the fact that ship will perform a manoeuvre to avoid collision and the potential external influences. If we assume the kinematic status of both ships are deterministic and known regardless of its variation, the positions of ship A and B at any time after step t can be presented according to Eq. 3.5, respectively:

$$\begin{aligned} P_A(t) &= P_A(t_0) + \int_{t_0}^{t} V_A(t)\,\mathrm{d}t \\ P_B(t) &= P_B(t_0) + \int_{t_0}^{t} V_B(t)\,\mathrm{d}t \end{aligned} \tag{3.1}$$

Eq. 3.5 can be then rewritten into Eq. 3.6:

$$VO_{A|B} = \bigcup_{t}^{\infty} \left(\frac{P_B(t) - P_A(t_0)}{(t-t_0)} \right) \oplus \frac{ConfP}{(t-t_0)} \tag{3.1}$$

Where $P_B(t)$ is the known position of Ship B at time t after the start point t_0, and $P_A(t_0)$ is the position of ship A at start time point t_0. $\left(\frac{P_B(t)-P_A(t_0)}{(t-t_0)} \right) \oplus \frac{ConfP}{(t-t_0)}$ is the condition for the collision to happen at time t.

Compared with original LVO, this non-linear approach, which is proposed by Large et al. (Large et al., 2002) has loosened the original assumption that both ships maintain their kinematic status throughout the encounter process. With this improvement, the kinematic status of the target object can be updated during the process of collision risk detection combined with AIS data. The graphical interpretation of NLVO is shown in figure 3.3:

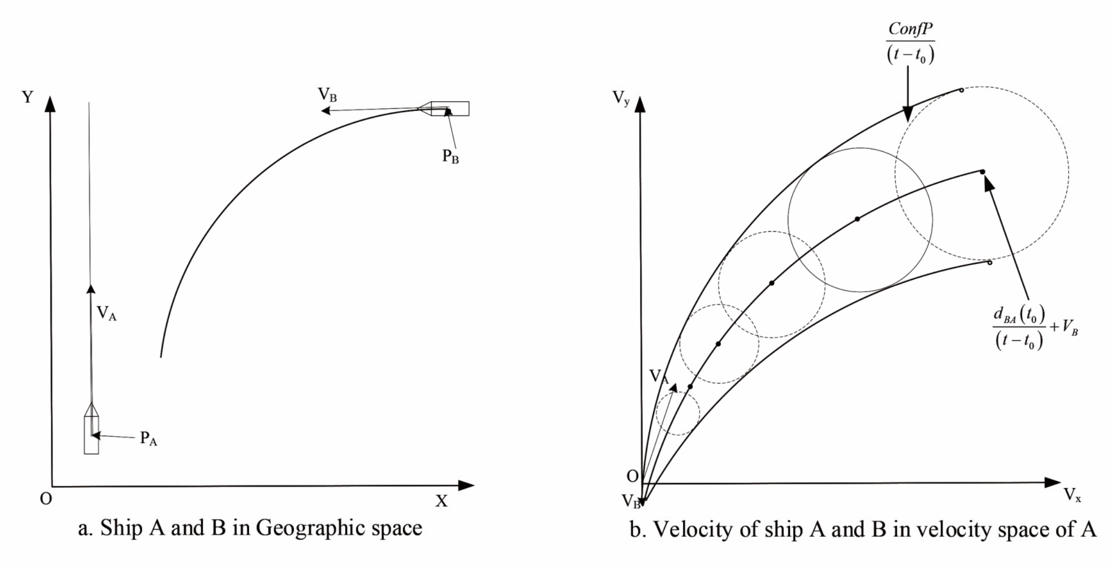


Figure 3.3 Graphical interpretation of NLVO

3.3 Model for Collision Candidate Detection

3.3.1 Basic Two-ship Encounter Scenario

For collision candidate detection method, this research chooses NLVO as the approach to fulfilling the objective with the integration of ship AIS data. AIS is a data exchange system that broadcasts information of the individual ship (static information, e.g. length, width; dynamic information, e.g. location, speed over ground, course over ground, heading, etc.; and voyage related information, e.g. destination) from one to another at interval from 2s to 6 mins (ITU, 2014). With its large-scale worldwide application, AIS serves a significant role in many aspects and boosts research on collision risk analysis, etc. (Tu et al., 2017). In this chapter, AIS data is integrated into the method as the main data source.

To design the collision candidate detection method, an NLVO based detection algorithm is firstly proposed. For any given instance t_i , after time step t_0 , $\mathrm{VO}_{\mathrm{A|B}}$ can be expressed by Eq. 3.7:

$$\mathrm{VO}_{\mathrm{A|B}_{t_i}} = \left(\frac{P_B(t_i) - P_A(t_0)}{(t_i - t_0)} \right) \oplus \frac{ConfP}{(t - t_0)} \tag{3.1}$$

Where $\mathrm{P_B}(\mathrm{t_i})$ is the position of ship B at t_i and $\mathrm{P_A}(\mathrm{t_0})$ is the position of A at time step t_0 , $ConfP$ is the circular conflict area. For engineering practices, it is plausible to introduce more complex, and regional dependant shapes of the domain as criteria. However, for simplicity of calculation and the focus of this chapter is the introduction of the velocity obstacle algorithm into research on collision candidate detection, here we utilise a circular area with pre-set diameter. Based on Eq. 3.7, a Time-Discrete Non-linear Velocity Obstacle (TD-NLVO) for collision candidate detection algorithm is designed as algorithm 1 illustrates:

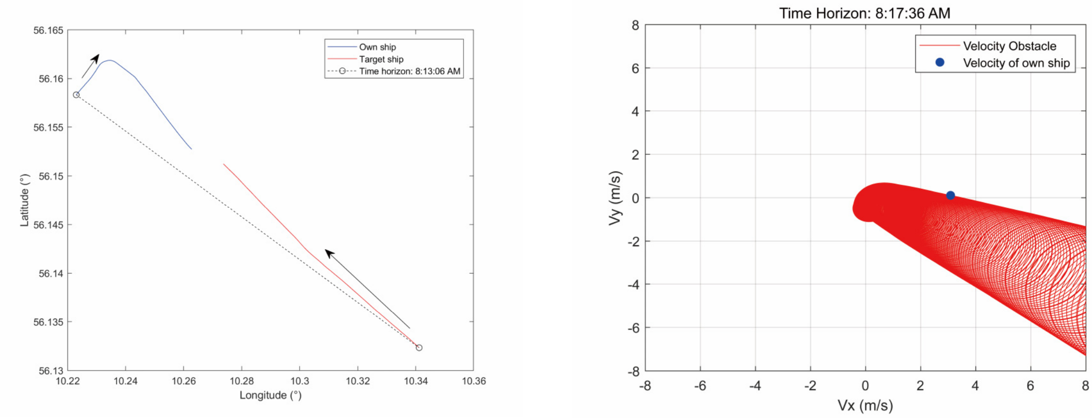
Algorithm 1 Time-discrete Non-Linear Velocity Obstacle for Collision Candidate Detection

---

Input: AIS data of ship A and B;
for P_i in trajectory A
  for P_j in trajectory B and $P_j.time \geq P_i.time$
    R_ConfP= P_i.length+P_j.length ;
    Dist=$\left\| P_i - P_j \right\|_2$;
    CenterofsVO = Dist/(P_j .time- P_i .time));
    RadiusOfsVO = R_ConfP /(P_j .time- P_i .time));
    Determine=$\left\| P_i.velocity - \text{CentreofsVO} \right\|_2$ - RadiusOfsVO;
    if (Determine≤0)
      Violation.DetectTime=P_i .time;
      Violation.ViolationTime= P_j .time;
    end if;
  end for;
    if(Violation$\neq$ [])
     Process.detection_time= Violation.DetectTime;
     Process.start_of_violation=min(Violation.ViolationTime);
     Process.end_of_violation=max(Violation.ViolationTime);
    end if;
end for;
  if (Process$\neq$ [])
      if Process.detection_time is continuous
        start_of_detect=min(Process.detection_time);
        end_of_detect=max(Process.detection_time);
        start_of_violation=max(Process.start_of_violation);
        end_of_violation=max(Process.end_of_violation);
      Output: MMSIs of A and B, detect period, and violation period;
      else
          foreach subsets where Process.detection_time is continuous
            start_of_detect=min(Process.detection_time);
          end_of_detect=max(Process.detection_time);
          start_of_violation=max(Process.start_of_violation);
          end_of_violation=max(Process.end_of_violation);
     Output: MMSIs of A and B, detect period, and violation period;
      End if;
  End if;

The principle of the algorithm is that: for two ships' AIS data, choose A as own ship, and B as the target. Secondly, take every data point P_i in trajectory A as the step t_i , and calculate the velocity obstacle set induced by point P_j in trajectory whose time is later than t_i , according to Eq. 3.7. Then, check if the velocity of ship A at a time t_i falls into this set. If so, the time information (start and end time of the violation, time of detection instance) will be stored as timespan of violation and detection instance at a time step t_i . Detection time is the information about the start and end of the detected VO violation. If the VO violation was detected by the algorithm, the corresponding time would be recorded based on AIS data of the own ship. Duration is the period for the existence of. For every data point P_j in trajectory B repeat such procedure and store all this time information to construct the time span of VO violation.

For every data point P_i this whole procedure will be repeated. Finally, combine all the result of the determination of every point in trajectory A to see if there is any VO violation. If any VO violation was detected between two ships, they would be determined as a collision candidate and time span of the violation will be collected as a record. To avoid duplicate detection of the same encounter situation due to potential fluctuation of VO violation and possible delayed AIS data, here we introduced a time threshold $T_{linking}$ ("linking threshold") as criteria to determine whether two timespans of VO violation can be determined as one encounter process, by checking if the time difference between two parts is less than $T_{linking}$. Since this parameter could have an influence on the results, and it is highly dependent on the quality of the data collected, to set the value for it, the frequency of AIS data must be considered. Based on the data we collected and cleansed, we have identified that over 98.5% of the data are transmitted within 30s. Therefore, here we choose 30s as the threshold between VO violation, if the second VO happened within the 30s after the last one, they would be defined as one. Figure 3.4 illustrates an example of TD-NLVO between two ships at a certain time instance.



(a) Trajectories of two ships (b) Velocity obstacles induced by the target ship

Figure 3.4 Illustration of TD-NLVO between two ships at time point

In figure 3.4, the circles indicate all the velocity obstacles induced by ship B after time step t_i, and the blue dot shows the velocity of ship A at t_i. If the blue dot falls into any velocity obstacle, the criteria that both ships approach each other closer than the predefined safe distance will be satisfied at a certain time t. For every point in trajectory A, such calculation will be performed to verify if VO violation exists and how long did it last. However, due to data are transmitted in a discrete manner with uneven time intervals, in some cases, the time between two data points would be too long that their velocity obstacles are "too far" from each other. To avoid the situation that velocity of own ship could fall into the velocity space between two velocity obstacle sets, a linear interpolation technique is introduced to obtain the intermediate VO sets between them when the time interval between two data points is too large.

With the development of the maritime industry, vessel traffic in ports and waterways are increasing and intense in some water areas, which results in a huge amount of AIS data. To reduce the computational time and obtain the result of collision candidate detection when a large amount of data, e.g. one year of data are analysed. Data are divided into multiple subsets with **Scanning interval** T_{Scan}. Data within this interval will be gathered as subsets to apply the designed algorithm. Under such configuration, the collision candidate detection method for ports and waterways are designed according to the flowchart in figure 3.5.

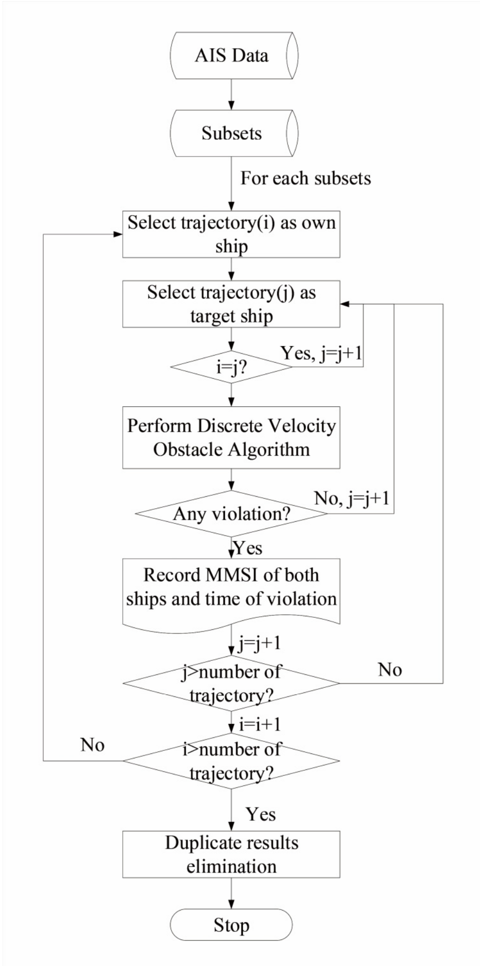


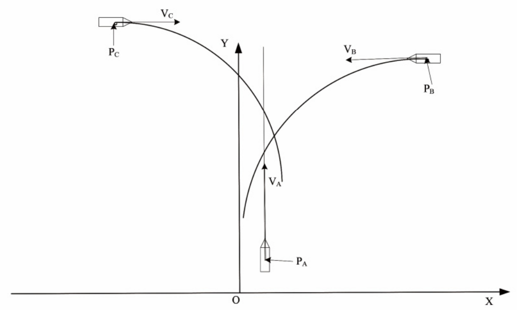
Figure 3.5 Flowchart of the proposed collision candidate detection method

3.3.2 Multi-ship Encounter Scenario

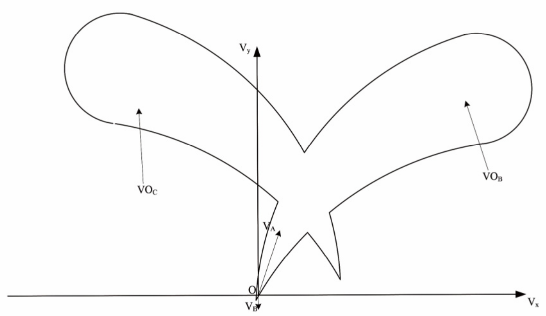
1) Research Design

For ships navigating in water areas with heavy maritime traffic, e.g. busy ports and important waterways, the encounter situations are complicated when multiple ships (more than 2) are involved. Due to the fact that the International Regulations for Preventing Collisions at Sea (COLREGs) only provides rules and guidance for collision avoidance between two ships, such situations require the Officers On Watch (OOWs) to evaluate and prioritize the risk of collision caused by each individual encounter and propose and execute a global avoidance manoeuvre to safely pass the target ships. During this process, the decision-making process and their room to manoeuvre is also constrained by the influence of multiple target ships, which increases the risk of collision in such situation, compared with the simple encounter where only 2 ships are involved.

To better grasp the picture of the collision risk in certain regions, it is necessary to analyse the collision candidates/near misses with more detail. A multiple encounter situation detection procedure is proposed based on the Boolean operation "Union" on the polygons. A simple illustration is shown in figure 3.6:



a. Ship A, B, and C in Geographic space



b. Velocity of ship A and B in velocity space of A

Figure 3.6 illustration of multiple encounter situation and Boolean operation on polygons

Suppose that ship A, B, and C are in an encounter situation shown in figure 3.6 (a), and their kinematic information is known. Based on the traditional analysis method, such a situation will be decomposed into two situations and be analysed separately, which will result in a redundant record in the collision candidate list. To solve this problem, here the Boolean operation on polygons is introduced. The velocity obstacles of ship A induced by B and C can be merged as one as indicated by figure 3.6 (b), which allows ship A to evaluate if her velocity has violated the combined NLVO. The individual NLVO induced by each target ship will be utilised to determine which target ship has contributed to such violation. The Boolean operation on polygons is a popular technique in computational graphics and geosciences. A complicated shape can be generated with multiple polygons using the Boolean operation such as "union" (combine), "intersect", etc. (Martínez et al., 2009). In this research, such a technique is introduced to perform the combination of NLVO sets with open software libraries such as "PolyBoolCS[3]" "polybooljs[4]". To do this, each VO induced by the data point of a target ship is first discretized as a polygon shape of 20 points, then the "union" operation is performed to combine the separated VOs as a large area, which represents the individual NLVO induced by

[3] https://github.com/StagPoint/PolyBoolCS

[4] https://github.com/voidqk/polybooljs

a target ship. On the basis of the individual NLVOs, one or multiple combined NLVO will be obtained to represent the multiple encounter situation in the velocity domain of the own ship.

2) Model Establishment

As one of the critical elements in probabilistic risk analysis of ship collision accident, identification of collision candidates/near misses is the first step to quantify the risk and its characteristics. For that purpose, the TD-NLVO and Boolean operation on polygons are integrated into this research. A modified criterion of collision candidates, as shown in Eq. 3.8 is introduced as the basis of the algorithm:

$$\begin{aligned} \mathrm{VO}_{\mathrm{A}} &= \bigcup_{j=1}^{n} \mathrm{VO}_{\mathrm{A}|\mathrm{Ship}_{j\,t_i}} \\ \mathrm{VO}_{\mathrm{A}|\mathrm{Ship}_{j\,t_i}} &= \left(\frac{P_{Ship_j}(t_i) - P_A(t_0)}{(t_i - t_0)} \right) \oplus \frac{ConfP_{Ship_j}}{(t_i - t_0)} \end{aligned} \tag{3.1}$$

where VO_{A} is the non-linear velocity obstacle sets of the own ship (ship A) induced by the other ships in the encounter situation, which is the union of all non-linear velocity obstacle sets induced by each target individually, t_0 is the time of detection, and t_i is the future time step. Each non-linear velocity obstacle set induced by one target ship (Ship_j) is obtained following the criterion in the previous work, with the circular shape of ConfP. In principle, one can also use other shapes of criteria for collision candidate detection, e.g. elliptical ship domain, etc. However, since the goal of this chapter is to propose the method that can detect multiple ship encounter, the basic shape of the criteria is considered here. It is also plausible to apply other complicated shapes of the criteria, e.g. elliptical ship domain, etc. into the algorithm, considering the local ship traffic characteristics when in practices. Based on the criteria of Eq. 3.8, an improved TD-NLVO for the multi-ship encounter is proposed as Algorithm 1 illustrates (for a three ships encounter scenario):

Algorithm 2 Ship domain-based Time-discrete Non-Linear Velocity Obstacle for multi-ship encounter detection

Input: AIS data of ship A (own ship) and target ship 1,2, … n;
for P_i in trajectory A
for every target ship j
    for P_m in AIS data of target ship j where $P_m.time \geq P_i.time$
        Radius of ConfP=500 m;
Calculate the distance between own ship and target ship j;
Calculate the centres of ConfP of target ship j;
List<ConfP> NLVO_ship_j.Add (ConfP);
end for;
individual_NLVO_ship_j=Boolean operation (NLVO_ship_j);
List<Polygon> individual_NLVO.Add(individual_NLVO_ship_j);
List<MMSI> name_of_target_ship.Add(name_of ship_j);
end for;
Combined_NLVO_i=Boolean operation(individual_NLVO);
Store the data of individual VOs and corresponding ship names;
List<polygon> combined_VO.Add (Combined_NLVO_i);

```
end for;

if (combined_NLVO ≠ [])
  for each Combined_NLVO_i
     determine if the velocity of own ship at each moment violate the combined NLVO;
        if (violation==true)
           store the time and name of own ship and the shape of the combined NLVO;
           determine which individual ship contribute to the violation;
           store the contributor and its individual NLVO;
        end if;
  end for;
end if;

if (violation of combined NLVO ≠ [])
```
Output_1: Record of violation of combined NLVO at each data point of own ship A (time, true or false of the violation, true or false of the multiple-violation, the shape of the combined NLVO);
Output_2: Record of violation of individual NLVO at each data point of own ship A (name of the contributor, shape of the corresponding individual NLVO);
end if;

The principle of the algorithm is as follows: Suppose that ship A, and multiple ships are in an encounter situation. Ship A is selected as the own ship. For each data point P_i of ship A's trajectory, set $P_i.time$ as the detection time for this point. All the AIS data of the target ships whose time is later than $P_i.time$ are collected and are transformed into NLVOs induced by them according to Eq. 3.8. For each target ship j, each discrete ConfP induced by the data point in the AIS data will be obtained using Eq. 3.8, and all the ConfP are combined as one individual NLVO using Boolean operation on polygons to represent the NLVO induced by the target ship j at $P_i.time$. During the process, the ConfP are firstly discretised as polygons with 20 points and then developed with the Boolean operation. When all the individual NLVO induced by target ships are obtained, the combined NLVO, which represents the multiple encounter situation at $P_i.time$ is obtained with the help of the union operation. The velocity of own ship will be analysed to determine if there is a violation of the combined NLVO. If so, the time and the ship name which caused the NLVO violation will be recorded for further analysis. The individual NLVO violation detection will be further performed to decompose the multi-ship encounters into pairwise analysis between the own ship and each of the target ship, to verify if there are multiple violations with target ships and determine the contributor to the encounter situation. With such design, the encounters with the participation of multiple ships (more than 2) can be identified from the historical AIS data to facilitate the estimation of the geometric collision probability in the waterways with more insights on the characteristics of ship encounters. In the meantime, the analysis of the multi-ship encounter could also be beneficial for the collision avoidance of the individual ships. However, due to the scope of this research, interested readers on such a topic, please be referred to (Huang et al., 2019b) for details.

3.4 Case Studies

In this section, a series of the case study is conducted to verify and illustrate the capability of NLVO-based approach on identifying the collision candidate in historical AIS data and its details.

3.4.1 Data for Case Studies

In this section, a series of the case study is implemented to verify the efficacy of the TD-NLVO algorithm on the individual encounter process and implementation of the methods on waterway collision risk analysis, respectively. To do this, historical AIS data in Port Aarhus, Denmark within the boundary: Latitude: 56° 6.012’ N to 56° 12.012’ N and longitude: 10° 11.982’ E to 10° 21.972’ E are collected thanks to the open-access provided by Danish maritime authority. The time illustrated in the manuscript is obtained directly from the AIS data, which is the local time (UTC+1).

In section 3.4.2, 1 case of ship encounter is illustrated to demonstrate the capability of the proposed TD-NLVO algorithm on identifying the two-ship encounter situation. This is to illustrate how the TD-NLVO algorithm detects the encounter process and identifies collision candidates. In section 3.4.3, two case studies were performed to verify the capability of the proposed method for detecting multi-ship encounter process. Case 1 is an encounter situation where four ships are involved, and the own ship has a multiple encounter situation with two of the target ships. Case 2 is a more complicated encounter situation where multiple ships are involved, and the own ship has VO violation processes with multiple target ships at the same time.

3.4.2 Simple Encounter Situation

In this case, two ships with MMSI (Maritime Mobile Service Identifier) “218XXX000” (Own ship), “219XXX261” (Target ship) from 11th March 7:00 AM to 8:00 AM are chosen as research objects. Their AIS data are collected to apply the TD-NLVO algorithm on. The details of these two ships and data and trajectories can be found in table 3.1 and figure 3.7, respectively:

Table 3.1 Information about research objects

MMSI	Type	Length (m)	Width (m)	Duration of data
218 XXX 000	Cargo	82	11	11/03/2018 7:13:09 to 7:59:57
219 XXX 261	Dredging	30	8	11/03/2018 7:29:16 to 7:59:50

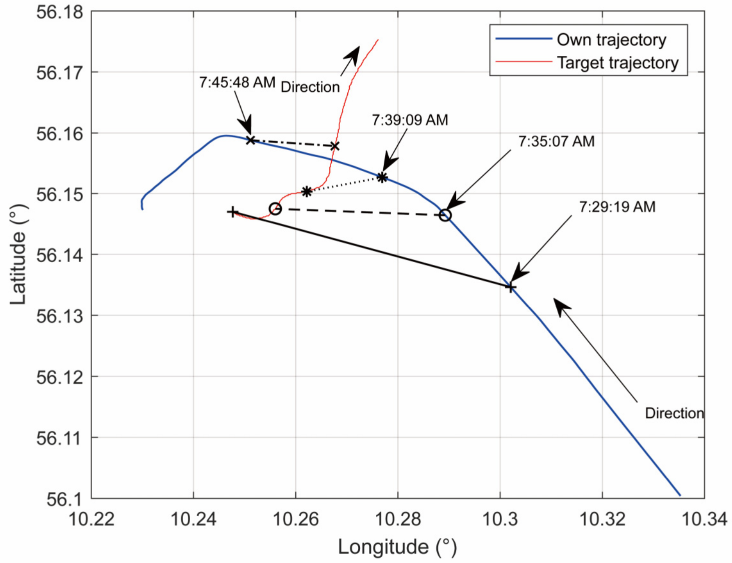


Figure 3.7 Trajectories of two ships

When applying the algorithm, two parameters: R , and $T_{\text{threshold}}$ are defined as $R = 1000\ \text{m}$ and $T_{\text{threshold}} = 30\text{s}$, respectively. Figure 3.8 shows four snapshots of VOs of “218XXX000” induced by “219XXX261” at different time steps.

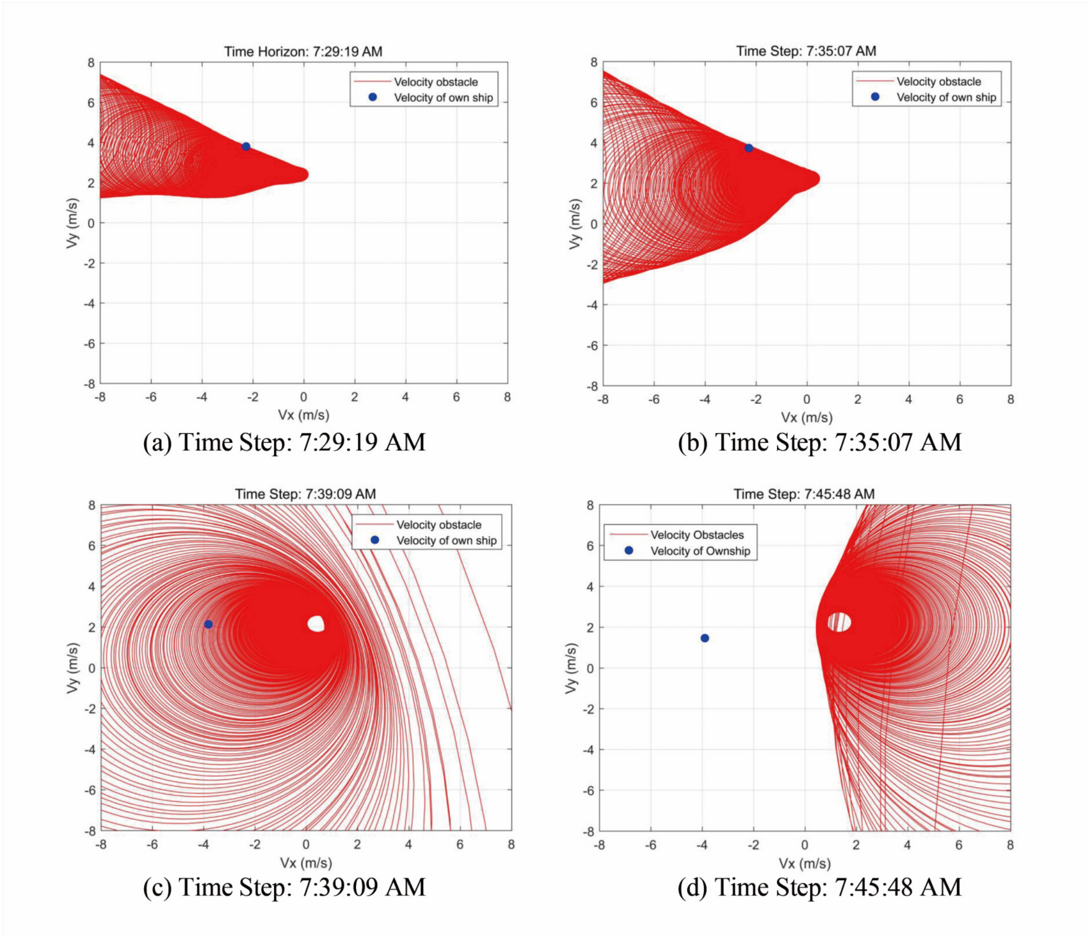
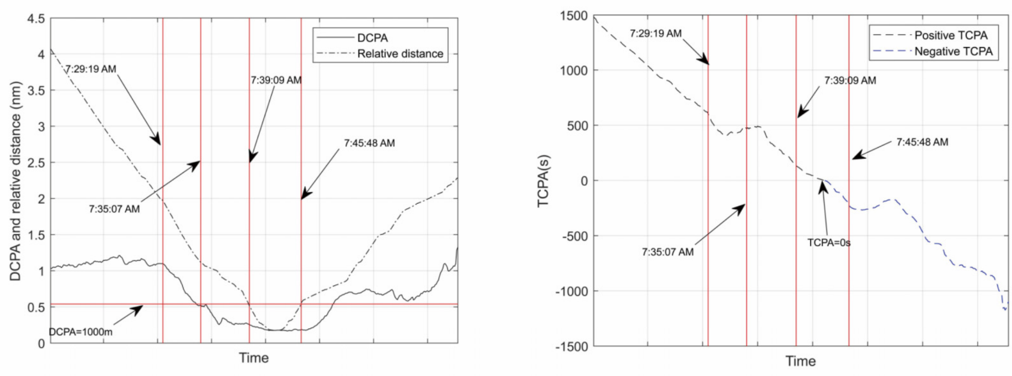


Figure 3.8 Snapshots of VOs during encounter process

In figure 3.8, the blue dot represents the velocity of own ship at a given time step while the family of red circles are the Velocity Obstacles induced by target ship after the time step. We can find that VOs induced by target ship are constantly changing. If the blue dot falls into any VOs, violation of safety region of two ships will happen at the certain time, i.e. based on the information at a time step t_0 , a violation of safety region will happen at a certain time thereafter. For example, figure 3.9 (a) indicates that at time step 7:29:19 AM, a VO violation is detected. From then on, continuous violations of VOs are detected in succession, which together constructs the result that the algorithm detects VO violation induced by target ship during 7:27:28 to 7:41:55 AM and the duration time of such violation is 7:39:04 to 7:42:05 AM.



(a) DCPA and relative distance

(b) TCPA

Figure 3.9 DCPA, relative distance and TCPA of two ships during the encounter

Figure 3.9 shows DCPA, relative distance and TCPA of two ships and their changes during the process. DCPA fist dropped below the safety threshold (1000 meters) and then came back to safety while TCPA constantly decreased. However, although the general trend satisfies characteristics of the typical encounter, some small fluctuations of their values can be identified in the figures, which could lead to duplicate detection of the same encounter process when some methods which utilised indices like CPA parameter at certain instance as criteria, and time interval for detection are determined arbitrarily. This issue will be addressed in the discussion section.

We can also find that the duration of CPA parameters violation and VO violation is different. For example, at time step 7:29:19 AM a VO violation during 7:41:33 AM, and 7:42:05 AM was detection, which, however, is different from the result of CPA parameters where TCPA between two ships were already smaller than 0. This indicates that they already passed the closest point of approach at that time. The reason to explain this difference can be explained by the assumption in VO, that at each time step, the velocity of own ship is considered as constant, and the information of the future movement of own ship at that step is not considered into the algorithm. If own ship maintains its speed and course, there will be no difference between VO results and DCPA parameters, however, if own ship performs certain manoeuvres, especially collision avoidance manoeuvre, violation of VO will be postponed and finally out of detection period.

Another finding is the difference between VO violation and the actual relative distance between ships. During the encounter process, own ship could take certain collision avoidance manoeuvres when the risk of collision was detected. The effect of this manoeuvres reflected by data is two folds: 1) The duration of VO violation only has overlap with detection time, or even have no overlapping, which means the risk of collision is solved. 2) The actual violation of safe distance is not synchronized with detected VO violation, which means the actual violation of safe distance is later than VO detection. The reason for these two effects can be explained by the assumption of VO. Based on this finding, we propose three situations on the behaviour of ships during the encounter:

1. No VO violation at any time. The actual relative distance between each other is always larger than the threshold;
2. VO violation existed, but no overlap between detection time and VO violate duration. The actual relative distance between each other is always larger than the threshold;
3. VO violation existed, and the detection time has overlap with duration. The actual relative distance between two ships first reduced below the threshold and then increased above.

For the first situation, ships can be deemed to pass through each other safely. For the second situation, although VO violation was detected, ships did not approach each other closer than the threshold, which means the danger of collision did not emerge. Therefore, in the algorithm, this kind of results are treated as false positive and are excluded.

3.4.3 Multi-ship Encounter Situation

The objective of these case studies is to verify the effectiveness of the proposed algorithm and the trade-off between the computational time and duration of the data input. Here we utilised two different sets of data for 15 mins each as test data sets. The description of the data sets is shown in Table 3.2.

Table 3.2 Description of the test data

No.	Duration of Data	Own ship	Ships involved
1	4-10-2018 9:45 to 10:00	219XXX172	219XXX307, 219XXX172, 304XXX000, 578XXX100
2	26-10-2018 4:45 to 5:00	219XXX000	219XXX543, 219XXX416, 219XXX477, 219XXX903, 219XXX000, 219XXX000, 231XXX000, 304XXX688, 304XXX000,

1) Case 1

In this case, 15 mins of AIS data are utilised to test the proposed method, where “219XXX307, 219XXX172, 304XXX000,578XXX100” are the ships involved in the duration. “219XXX172” was chosen as the research object (Own ship). To apply the proposed algorithm, the radius of the safety region is set as 500 meters. Based on the results of the method, a multi-ship encounter between the own ship “219XXX172” and target ships “578XXX100” and “304XXX000” was detected. Table 3.3 and figure 3.10 illustrate the results of encounter detection and a snapshot of positions of ships, combined NLVO of own ship induced by target ships, and Violated NLVO of the target ship:

Table 3.3 Description of VO violations

No.	MMSI of VO violation	Detection period	Description
1	219XXX172, 304XXX000	9:46:23 to 9:48:57	Individual violation
2	219XXX172, 578XXX100	9:45:35 to 9:52:50	Individual violation
3	219XXX172, 304XXX000, 578XXX100	9:46:23 to 9:48:57	Multiple violation
4	219XXX172, 578XXX100	9:46:23 to 9:52:50	Individual violation

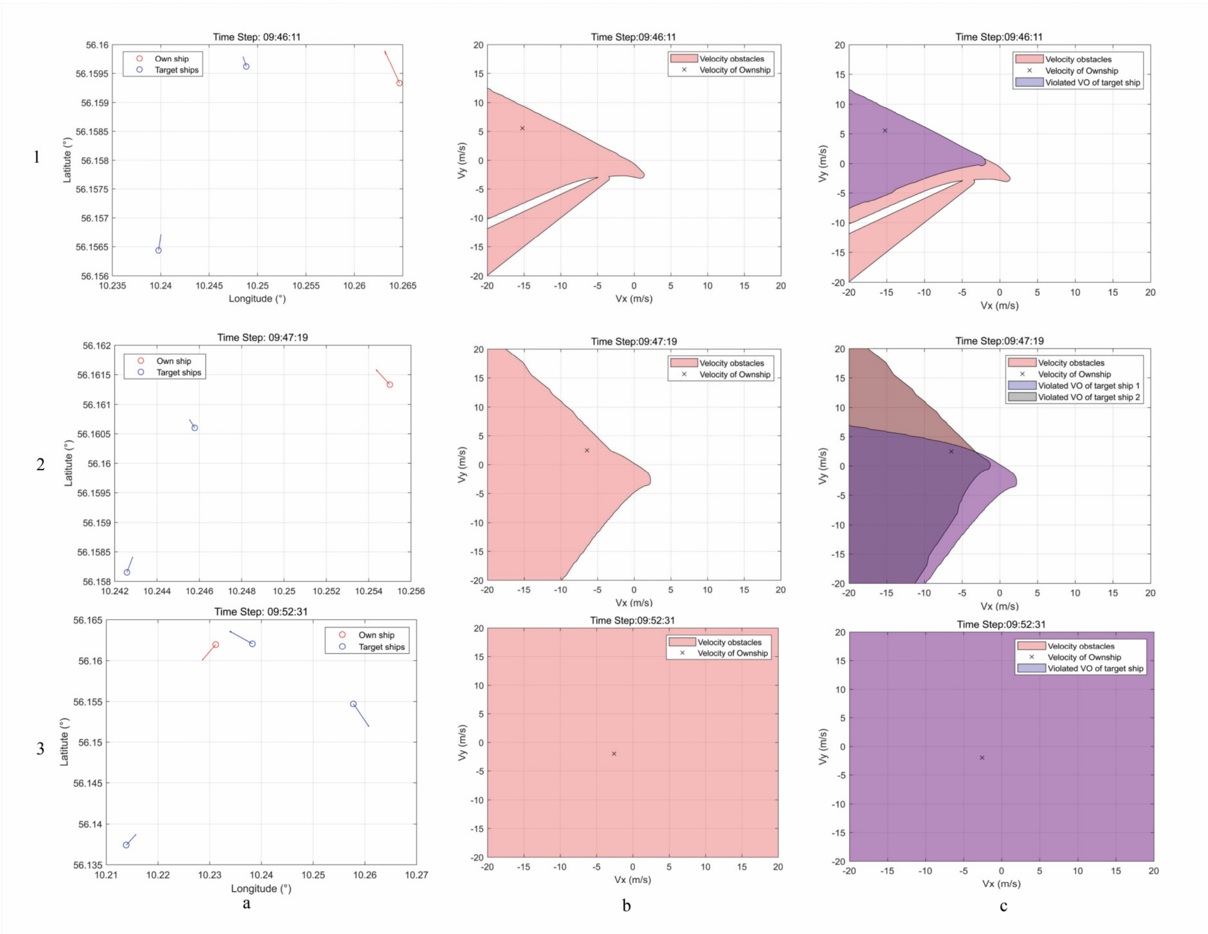


Figure 3.10 Positions and VOs of ships at different time steps – scenario 1

From table 3.3, one can see that the own ship has the violation of the combined non-linear velocity obstacle sets and individual violations with both two target ships within the detection time span, respectively. The duration of detected NLVO violation for the two ships is different, and they share an overlap in time, which means that during the encounter process there was a period of time the own ship has violated the individual NLVOs at the same time. These findings can be confirmed in figure 3.10. In figure 3.10, the positions of ships at each time step, and the combined NLVO of target ships are shown in the column a and b, respectively. The decomposed NLVO to represent the violation of NLVO induced by each target ship are shown in column c. It is clear that the combined NLVO of target ships is composed of multiple individual NLVOs of each target ship. From figure 3. 10 (1, b) and (1, c) one can see that the violated NLVO induced by ship "578XXX100" is smaller than combined NLVO, and the results indicate that own ship only has violation with "578XXX100". This indicates that the NLVO of other targets is "combined" into the large NLVO during the Boolean operation

“Union” and the velocity of own ship does not have violation with them. As for figure 3. 10 (2, b) and (2, c), one can see clearly the combined NLVO is made by two different individual NLVOs showed in (2, c) and the own ship has the violation of each individual NLVOs. As for figure 3. 10 (3, b) and (3, c), one can see that the velocity space of the own ship is filled by the NLVO. This indicates that the current spatiotemporal proximity already satisfied the pre-set criteria. With this design of algorithm, the collision candidate detection process can be processed in this manner: firstly, determine if there is a violation of combined NLVO at each step, if there is a violation, then determine which individual ship caused such violation with the own ship. In this way, a detailed analysis of the encounter process can be conducted.

2) Case 2

In the previous section, a case scenario where the own ship has velocity violation of the non-linear velocity obstacle sets induced by two target ships is illustrated. Here a more complicated situation where multiple ships are involved in the encounter scenario is utilised to illustrate the capability of the proposed algorithm to detect multi-ship encounter process. The results of collision detection and a snapshot of positions of ships, combined NLVO, and violated individual NLVO or target ships are shown in Table 3.4 and figure 3.11, respectively:

Table 3.4 Description of individual VO violations – scenario 2

No.	MMSI of VO violation	Detection period	Description
1	219XXX000, 219XXX903	4:45:07 to 4:50:33	Individual violation
2	219XXX000, 231XXX000	4:45:07 to 4:55:47	Individual violation
3	219XXX000, 304XXX000	4:45:07 to 4:58:18	Individual violation
4	219XXX000, 219XXX903, 231XXX000, 304XXX000,	4:45:07 to 4:50:33	Four ships violation
5	219XXX000, 231XXX000, 304XXX000	4:50:37 to 4:55:47	Three ships violation
6	219XXX000, 304XXX000,	4:55:57 to 4:58:18	Individual violation

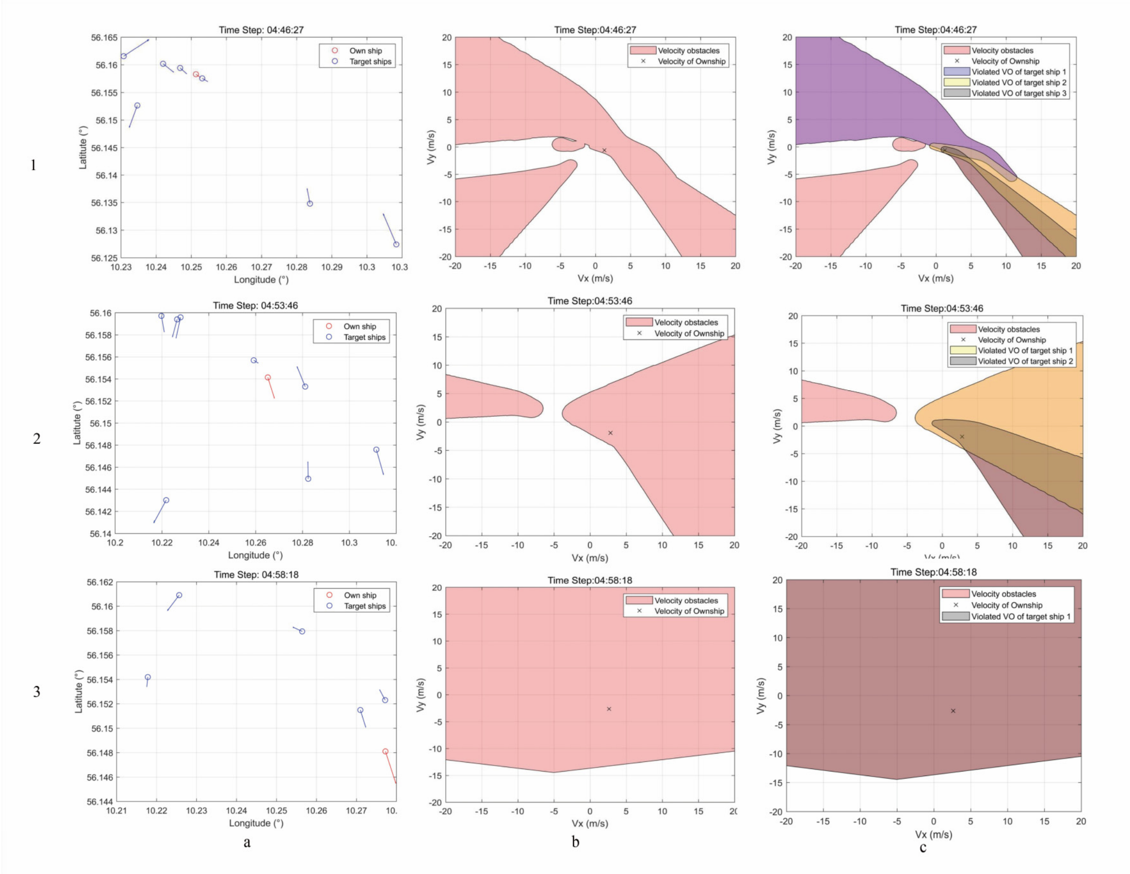


Figure 3.11 Positions and VOs of ships at different time steps – scenario 2

During the detection period, 9 ships participate in navigation in the water area. The own ship has violated the individual NLVOs of three target ships successively, as table 3.4 indicates. One can see that during the process, there are overlaps of time for the individual NLVOs violation period, which indicates that during such an encounter process, the velocity of the own ship has violated the NLVO induced by the multiple target ships simultaneously. The combined NLVO induced by the multiple target ships is decomposed and shown in the sub-figures in column c of figure 3.11. For example, during 4:45:07 to 4:50:33, the own ship and target ships “219XXX903, 231XXX000, 304 XXX 000” formulated a four-ship encounter that satisfied the criterion of collision candidates during the encounter process. This can also be proved in figure 3.11. From figure 3.11 (1, b) and (1, c), one can see at time step “4:46:27” the velocity of own ship violated the combined NLVO and especially, violated the NLVO induced by the ships “219XXX903, 231XXX000, 304 XXX 000” (figure 3.11 (1, c)). While at time step “4:53:46” one can see the velocity of own ship violated the VOs of the ship “231XXX000”, “304 XXX 000” simultaneously (figure 3.11 (2, c)). At time step “04:58:18” the own ship only had velocity violation with target ship “304 XXX 000”. Based on the results, one can see that the proposed method has successfully detected the multiple encounter situation during the encounter process. The detailed record of such an encounter can be utilised for further analysis of the characteristics of each phase of the encounter (e.g. single encounter-multiple encounter-single encounter, etc.).

3.4.4 Implementation for Waterway Risk Analysis

1) Collision Candidate Analysis

In this section, water areas of port Aarhus within the pre-set boundary is chosen as the research area. According to "Statistics Denmark"-the central authority on Danish statistics, the port of Aarhus is the second largest port in Denmark considering cargo throughput and largest container port, where maritime traffic is very active. In this case, 7 days of AIS data covering the research area are collected as test sets to perform collision candidate analysis. The parameters settings are as follows: T_{Scan} =60 mins ; $T_{threshold}$ =30 s ; and the diameter of the safety region is 1000 meters.

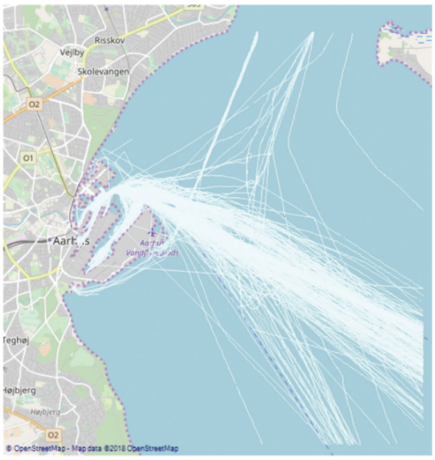


Figure 3.12 AIS trajectories within case study boundary

Figure 3.12 shows AIS trajectories of all ships navigating during the timespan. By applying the proposed method, collision candidates for 7 days are obtained. For example, Table 3.5 shows the results of the method. A detailed form of collision candidates on 11th March can be found in Appendix II.

Table 3.5 Results of the proposed method

Date	11-Mar	12-Mar	13-Mar	14-Mar	15-Mar	16-Mar	17-Mar
Number of collision candidates	24	40	63	46	58	99	29

In the sets of collision candidates, some own ships are detected to have violations of VOs with multiple ships, e.g. ship with MMSI "219XXX903" have VO violation with ship "249XXX000" and "305XXX000" during 8:00 a.m. to 8:10 a.m. Such results indicate a complicated encounter situation where multiple ships are involved.

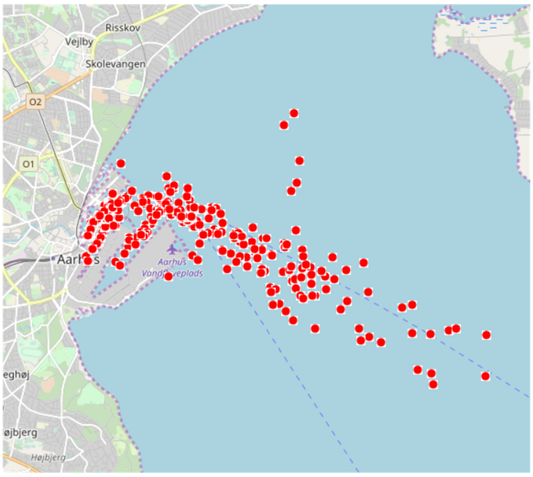


Figure 3.13 Spatial distribution of collision candidates

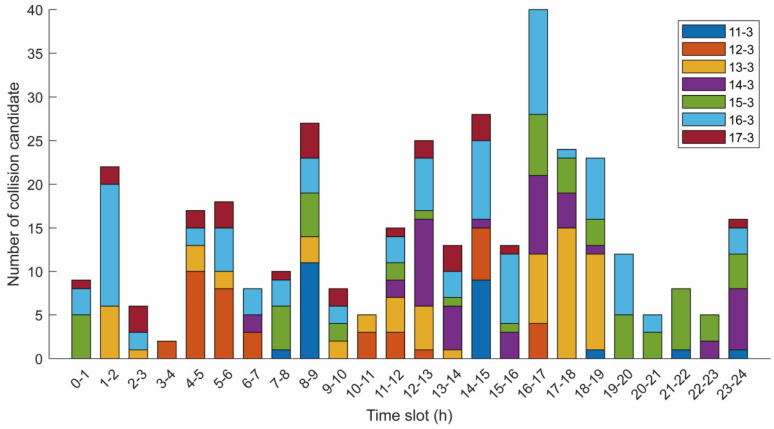


Figure 3.14 Temporal distribution of collision candidates

Figure 3.13 and 3.14 illustrate the spatiotemporal distributions of collision candidates within the area. We can see that collision candidates are unevenly distributed in the area, which clusters at port waters of Aarhus and ferry route from Aarhus to Sjaellands odde. According to the temporal distribution (Figure 3.14), a large number of collision candidates is detected during 1:00-2:00 a.m.,8:00-9:00 a.m., 12:00-13:00, 14:00-15:00, 16:00-17:00, and 23:00-24:00 p.m., this also matches the fact that route Aarhus to Sjaellands odde is a ferry route. Based on these findings, specific maritime safety management policies can be proposed.

2) Multi-ship Encounter Analysis

To further verify the proposed method on detection of multi-ship encounter situation, another data set which contains AIS data from 9:00 to 21:00 on Oct. 15th is utilised to identify the multi-ship encounter situations in the area of the case study. The original TD-NLVO are also introduced to make the comparison. The detailed information and their corresponding data obtained from TD-NLVO are also shown in Table 3.6 and 3.7, respectively.

Table 3.6 Multi-ship encounter obtained with the improved method

No.	Ships involved	Start time	End time
1	2497XXX00,2188XXX00,2587XXX00	15/10/2018 14:16:07	15/10/2018 14:16:31
2	2497XXX00,2188XXX00,2588XXX00	15/10/2018 14:20:44	15/10/2018 14:21:07
3	2588XXX00,2190XXX77,2587XXX00	15/10/2018 14:19:19	15/10/2018 14:24:15
4	2497XXX00,2188XXX00,2190XXX72	15/10/2018 14:31:41	15/10/2018 14:44:43
5	2497XXX00,2188XXX00,2190XXX72	15/10/2018 14:45:03	15/10/2018 14:46:03
6	2579XXX00,2091XXX00,2190XXX03	15/10/2018 15:49:29	15/10/2018 15:52:21

Table 3.7 Corresponding data obtained with previous TD-NLVO with each ship as own ship

No.	Own ship	Target ship	Start time	End time
1	2497XXX00	2188XXX00	15/10/2018 14:15:00	15/10/2018 14:29:54
	2497XXX00	2587XXX00	15/10/2018 14:16:07	15/10/2018 14:16:31
2	2497XXX00	2588XXX00	15/10/2018 14:20:44	15/10/2018 14:21:07
	2497XXX00	2188XXX00	15/10/2018 14:15:00	15/10/2018 14:29:54
3	2588XXX00	2190XXX77	15/10/2018 14:19:19	15/10/2018 14:23:26
	2588XXX00	2587XXX00	15/10/2018 14:16:19	15/10/2018 14:29:49
	2587XXX00	2588XX000	15/10/2018 14:24:15	15/10/2018 14:29:41
4	2497XXX00	2188XXX00	15/10/2018 14:30:00	15/10/2018 14:44:43
	2497XXX00	2190XXX72	15/10/2018 14:31:37	15/10/2018 14:44:43
	2188XXX00	2497XXX00	15/10/2018 14:34:16	15/10/2018 14:44:46
5	2497XXX00	2188XXX00	15/10/2018 14:45:03	15/10/2018 14:46:03
	2497XXX00	2190XXX72	15/10/2018 14:45:03	15/10/2018 14:46:10
6	2579XXX00	2091XXX00	15/10/2018 15:49:29	15/10/2018 15:53:41
	2579XXX00	2190XXX03	15/10/2018 15:48:04	15/10/2018 15:52:21

As Table 3.6 indicates, in total 6 cases of multi-ship encounter situations are identified from the AIS data, the start and end of the detection time are also included. According to the results and the aforementioned two cases of detailed illustration, one can see that the proposed improved TD-NLVO can identify the encounter situation where multiple ships are involved. Besides, as table 3.7 shows, for each case of a multi-ship encounter, the previous method has separately determined if the encounter between two ships violate the pre-set threshold. To obtain the information of possible multi-ship encounter, additional work has to be done to search for which ships have an encounter with multiple targets. Although such work could be conducted by searching in the results in table 3.7, there is a fundamental difference between the two methods: Within the design of the original TD-NLVO, the multi-ship encounter situation is decomposed into the pairwise analysis, as the other existing models for collision candidate detection do to simplify the detection process. However, the potential influence of other targets on the two encountered ships, which can be represented in the form of a united velocity obstacle in the velocity domain of the own ship, is also ignored as the method treats the encounters independently and equally. The difference may not be significant on obtaining the number of collision candidates, however, as the framework shows in Eq.1.1, the probability of collision also considers the causation factors, which can be influenced by the complexity level of the encounter situation as shown in (Chen et al., 2019b). By considering the multi-ship encounter situation and identifying them with historical AIS data, the information can be integrated into the causation risk modelling of collision. From this perspective, we think the consideration of multi-ship encounter within the design of the method is an improvement for probabilistic risk modelling of ship collision.

3.5 Discussion

3.5.1 Comparison between Classic Collision Detection Methods

For collision candidate detection using AIS data, one can find many existing methods from literature, e.g. Fuzzy ship domain method (Qu et al., 2011; Wang, 2010), projected ship domain methods (Chai et al., 2017), etc. Section 3.5.2 compared the results from TD-NLVO and CPA-based method with a different choice of parameters. In this section, 8 methods of collision candidate detection are evaluated to compare the results among them. The tested methods are shown in table 3.8:

Table 3.8 Description of test methods

Code	Name	Criteria
M1	TD-NLVO method	Encounter as a process; violation of Velocity obstacle sets
M2	CPA parameter method (DCPA, TCPA)	Encounter as a process; DCPA and TCPA thresholds
M3	Fuzzy ship domain method	Encounter as a process; the intrusion of Fuzzy ship domain
M4	Fujii ship domain method	Encounter as a process; the intrusion of Fujii ship domain
M5	CPA parameter method 2	Analysing at a time instance; DCPA and TCPA thresholds
M6	Projected ship domain method	Analysing at a time instance, the intrusion of ship domain
M7	Fuzzy ship domain method 2	Analysing at a time instance; the intrusion of fuzzy ship domain
M8	Fujii ship domain method 2	Analysing at a time instance; the intrusion of Fujii ship domain

The configurations for each method are as follow:

For M1, M2, M5, and M6 the diameter of the safety region is set to 1,000 meters;

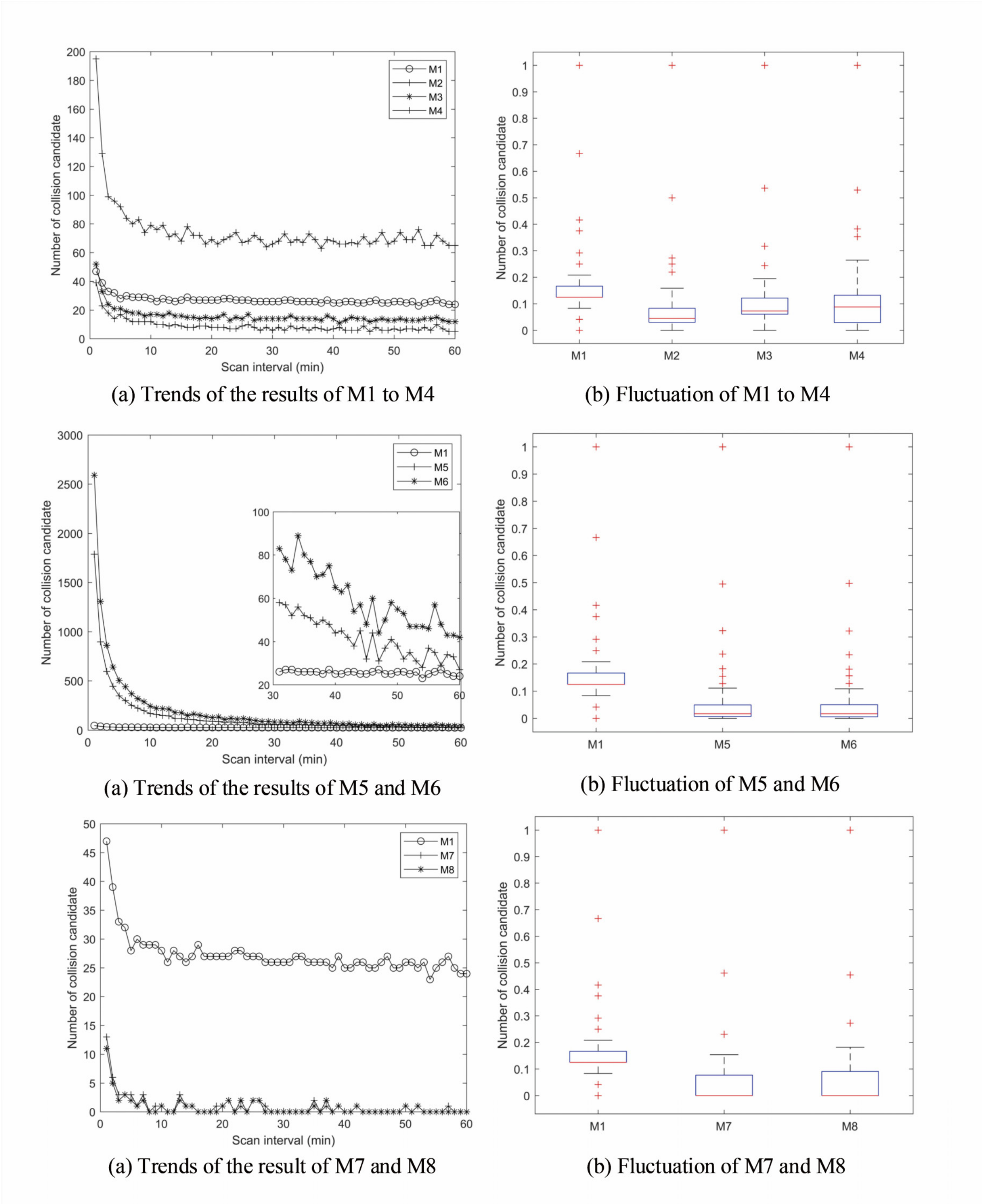
For M1-M4, linking threshold T_{theshold} is set to 30 seconds;

For M1-M4, the scanning interval T_{Scan} varies from 1 min to 60 mins;

For methods introducing Fujii ship domain: the length of major semi-axis is set to be 4 times of ship length, and minor semi-axis is set to be 1.6 times of ship length;

For methods introducing Fuzzy ship domain: fuzzy factor is set to 0.2.

Under such configurations, 60 tests for each method are conducted. Figure 3.15 gives the results of different methods:



(a) Trends of the results of M1 to M4
(b) Fluctuation of M1 to M4
(a) Trends of the results of M5 and M6
(b) Fluctuation of M5 and M6
(a) Trends of the result of M7 and M8
(b) Fluctuation of M7 and M8

Figure 3.15 Comparison between collision candidate detection methods

From figure 3.15 (a) and (b) one can find that T_{Scan} has a stronger influence on the results when T_{Scan} is less than 10 mins, after that, the decreasing rate for M1 to M4 which consider encounter as a process is relatively low. As for the absolute values of M1 to M4, we can find out that the results of M2 are constantly larger than the result of M1. This is because, for CPA parameter method using DCPA and TCPA value as criteria, due to the fluctuation of such value during the encounter, it is highly likely to obtain duplicate detection of the same encounter. Meanwhile, results from M3 and M4 is also relatively steady when T_{Scan} is larger than 10 mins, while their absolute value is lower than M1 and M2. This is reasonable since according to the parameters

M3 and M4 utilised, the ship domain utilised is smaller than the ConfP with a diameter of 1,000 meters. As for the fluctuation indicated by figure 3.15, (b) one can see that M1 is relatively more stable than M2-M4.

As for M5 to M6, we can find that results from these methods decrease dramatically when T_{Scan} is smaller than 20 mins. Although the fluctuation level is similar based on figure 3.15 (d), the absolute results' magnitude of these methods under different parameter setting varies from 10^1 to 10^3, which shows strong sensitivity to T_{Scan}. For M5 and M6, since encounter is assessed as a certain time instant, it is reasonable that long-duration encounter could be detected multiple times. M7 and M8 show a different situation where compared with M3 and M4, results of M7 and M8 are much smaller, which can be explained by the situation that for some dangerous encounter happening in between T_{Scan}, M7 and M8 failed to detect such situations.

Compared with M5-M8, M1 to M4 have relative higher reliability concerning T_{Scan}; meanwhile, M1's fluctuation is smaller than M2's (figure 3.15(b)). Due to the lack of a standard set of collision candidate and corresponding AIS data, we cannot conclude which method is "accurate", however, the advantage of considering encounter as a process and utilising VO as criteria are proved.

3.5.2 Parameter Sensitivity Analysis

In this section, TD-NLVO and CPA-based method are implemented to analyse their results under different choices of parameters.

As aforementioned, within the TD-NLVO method for collision candidate detection, two variables which may be determined manually are involved, which are: scanning interval T_{Scan} and linking threshold $\mathrm{T}_{theshold}$ respectively. The idea to include these two variables are 1) Divide large data set into multiple smaller subsets to reduce the computational time. 2) Reduce the chance of duplicate detections of the same encounter. However, in practice, such variables may have influences on the results. In this section, the influence of these two variables is analysed by performing 60 times of computation with different configurations. AIS data on 11st Mar. 2018 is utilised as test data.

The analysis is conducted in the following manner: 1) The first analysis concerns the influence of scanning interval T_{Scan} on the result. 60 times of computation with T_{Scan} varying from 1 min to 60 mins are performed, while other parameters, e.g. diameter of safety region and linking threshold $\mathrm{T}_{linking}$ remain the same. Figure 3.16 and 3.17 show the trend and fluctuation of the TD-NLVO method and CPA-based method using absolute and normalized results, respectively.

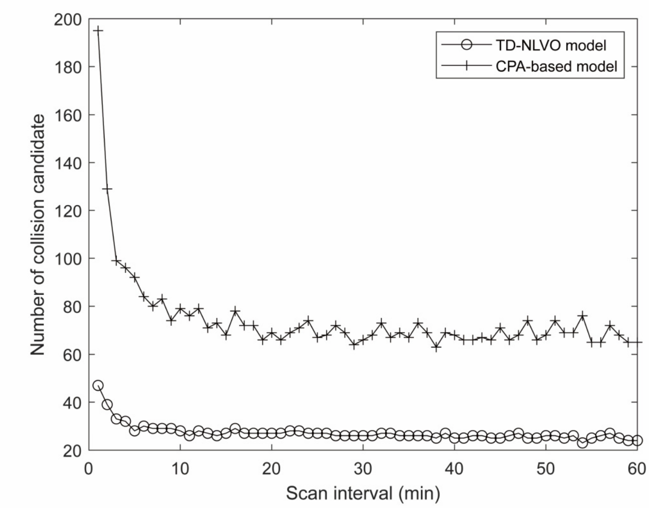


Figure 3.16 Trend of results concerning different values of the scan interval (min)

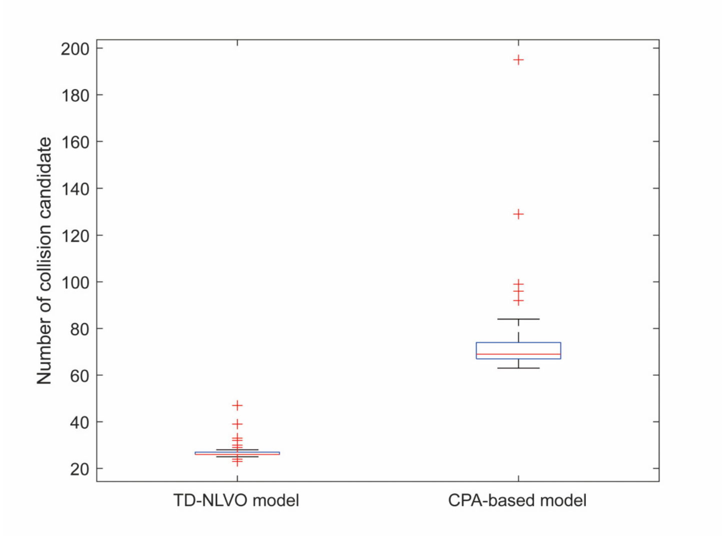


Figure 3.17 Fluctuation of the results

It is obvious that results from both methods decrease with the increment of T_{Scan} . This is because, for some encounters, their duration just cover the time spot dividing the dataset, which results in duplicate detection of the same encounter process. With the increment of T_{Scan} , the number of such situations continuously reduces. However, compared to the results obtained by TD-NLVO, the absolute result of the CPA-based method has a higher rate of duplicate detections. This can be explained by the fluctuation of DCPA and TCPA during the encounter process. The CPA-based method recognises one dangerous encounter as multiple short-duration encounters, divided by the fluctuation, while TD-NLVO method can alleviate such effects. As figure 3.16 illustrates, the CPA-based method has a larger fluctuation range compared to the VO method. This is also proved by the relative standard deviations of two methods which are 12.9% and 25.4%, respectively. Besides this, these figures also offer suggestions when applying the algorithm for detection in ports and waterways that value T_{Scan} should be larger than 20 mins to obtain reliable results.

As for linking threshold $\mathrm{T}_{linking}$, 60 sets of computation result with $\mathrm{T}_{Scan} = 60$ mins and $\mathrm{T}_{linking}$ varying from 30s to 1800 s are obtained, and the results are shown in figure 3.18. From the figure, we can see that the influence of $T_{linking}$ to the results is very small to the results. The relative standard deviation of the results is 3.06%.

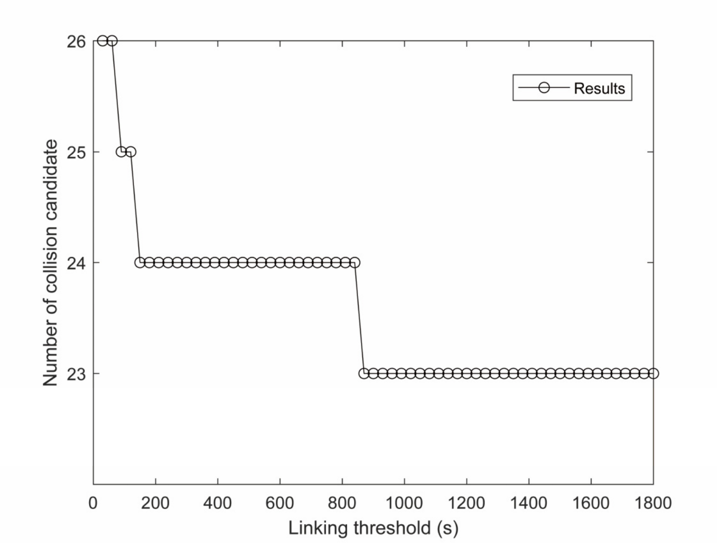


Figure 3.18 Number of collision candidates under the influence of $T_{linking}$

3.5.3 Re-run of the Methods

To test if the results fluctuate with multiple trials of the method, here we implement 20 times of rerun with the following configurations:

Data sample: AIS data on 11th March 2018;

T_{Scan} : 60 mins;

$T_{theshold}$: 30s;

The results are shown in figure 3.19:

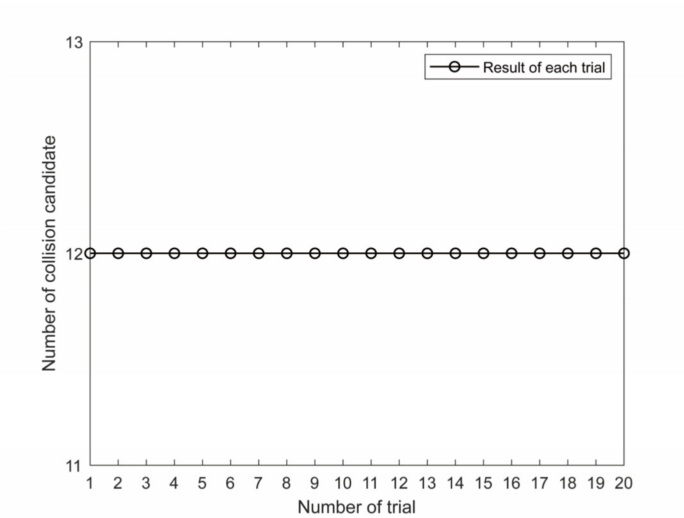


Figure 3.19 Results of repetition

According to figure 3.19, the results are consistent regardless of the multiple trials, which indicates such a method is reliable regarding this criterion.

3.5.4 Validation of the Multi-encounter Detection

In the previous sections, the improved TD-NLVO is proposed to identify the multi-ship encounter situations in the historical AIS data. The essence of VO and its variations is to project the spatiotemporal relationships between ships into the velocity domain of the own ship. It provides a different perspective to interpret the encounter situation, which does not change the nature of the encounter. Therefore, one of the alternative to verify the validity of the proposed method is to determine if the process of encounter also contains a period of time when the parameter such as DCPA violates the pre-set threshold. we utilised the traditional indicators DCPA, the relative distances and the TCPA on the two case studies to verify the validity of the proposed method. The results are shown in figure 3.20 and 3.21, respectively:

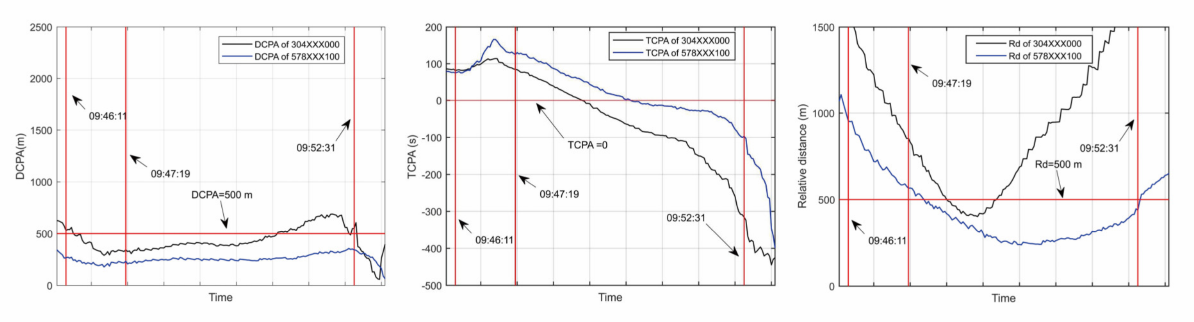


Figure 3.20 DCPA, TCPA, and relative distance of encounter scenario 1

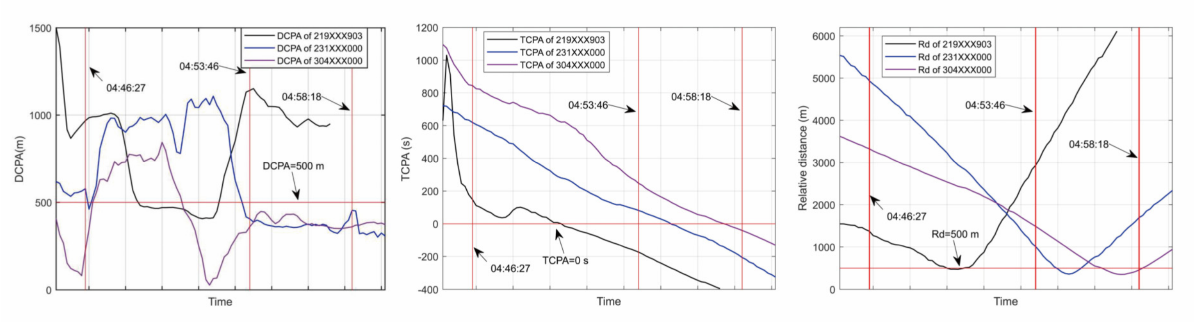
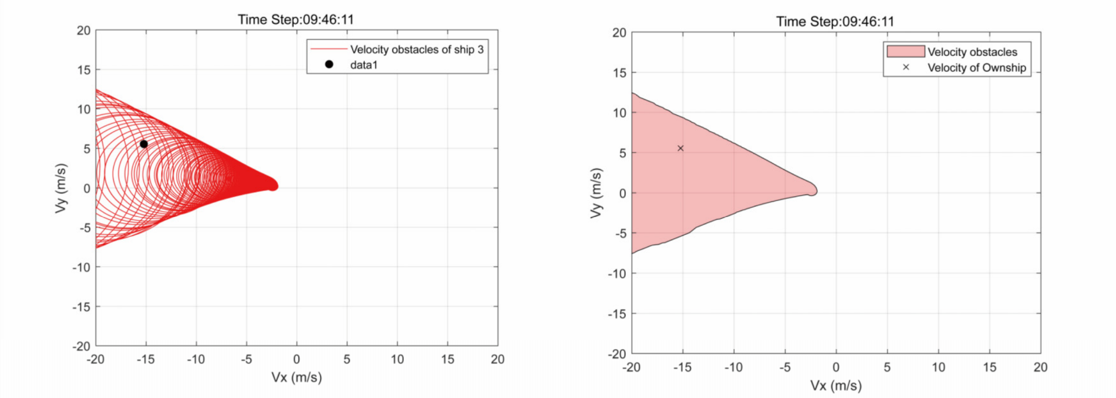


Figure 3.21 DCPA, TCPA, and relative distance of encounter scenario 2

As can be seen from figure 3.20 and 3.21, all the indicators (DCPA, TCPA and relative distance) fluctuate during the encounter process. As for encounter case 1, at time step 09:46:11 the DCPA between the own ship and target ship "578XXX000" is below the threshold while the corresponding TCPA and relative distance are above the threshold. These results indicate that the own ship and "578XXX000" could reach closer than threshold if they perform no avoidance manoeuvre, which is in consistence with the content in figure 3.10 (1,b) and 3.10 (1,c). At time step 9:47:19, both the DCPA between own ship and target ship "578XXX000" and "304XXX000" violate the threshold, while their TCPAs are positive, which indicate that the own ship will reach closer than threshold between both of them if they perform no avoidance manoeuvre, which is also in consistence with the content in figure 3.10 (2,b) and figure 3.10 (2,c). As for time step 09:52:31, the DCPA, TCPA and relative distance between own ship and target "304XXX000" are all below the threshold, which indicate they have pass clear from each other, as for the own ship and target "578XXX000", although the TCPA is negative, the relative distance between them is less than 500 m, which indicate they violate the pre-set safety boundary, which is still in consistence with the content in figure 3.10 (3,b) and figure 3.10 (3,c). As for encounter scenario 2, similar results can be interpreted from the figures. One thing that should be noted is that the indicators fluctuate significantly during the encounter process. As the previous research (Chen et al., 2018) indicates that such a process could be detected for multiple times if the encounter situation is analysed at a certain time interval, instead of the whole process. Figure 3.21 shows that although the DCPAs fluctuate significantly, their relative distances still smoothly reduce and then increase, which indicate that the encounter belongs to one process. Based on the comparison between traditional indicators and improved TD-NLVO, the validity of the proposed method is verified.

3.5.5 Comparison between the Standard and the Improved TD-NLVO

In the previous work by the authors (Chen et al., 2018), the VO sets of own ship induced by target ship at certain time step are represented as a family of discrete VOs, which is shown in figure 6 (a). This is caused by the discrete nature of historical AIS data, i.e. for each data point of target ship which is later than the detection time step, a VO is calculated and is collected into the VO sets for further violation analysis. The advantages of doing so are related to the simplicity of implementation; however, such procedure also introduced redundant calculation burden of violation detection at each time step. For each discrete VO in the NLVO set, it must be determined if the velocity of own ship falls into this NLVO, or not. One solution to this problem is to first combine the discrete VOs as one united shape, which is the actual NLVO of the own ship induced by the target, and then utilise this combined NLVO to perform collision candidate detection, e.g. the combined NLVO shown in figure 3.22 (b). To do this, the Boolean operation on the polygon in section 3.3.2 is introduced. The advantages of such procedure are as follows: 1) Compared with the previous TD-NLVO, the combined NLVO is more intuitive to understand the criterion of collision candidates. 2) For each time step of detection, only one determination of NLVO violation must be performed.



(a) Standard TD-NLVO (b) Improved version

Figure 3.22 Comparison between the improved algorithm (b) and TD-NLVO (a) on an individual encounter

Another improvement in this work is the consideration of multiple ship encounter scenarios in collision candidate detection. To realize the functionality to detect the multiple ship encounter, the Boolean operation is utilised again to combine the VOs induced by each target ships at each detection time step; To make the comparison between the functionality of the core algorithm between the previous TD-NLVO and the improved version in this research, The case 1 is processed with the TD-NLVO. The results are shown in Table 3.9 and figure 3.23, respectively.

Table 3.9 Results of the case obtained with TD-NLVO

No.	MMSI of VO violation	Detection period
1	219861000, 219022903	4:45:07 to 4:50:33
2	219861000, 231356000	4:45:07 to 4:55:47
3	219861000, 304903000	4:45:07 to 4:58:18

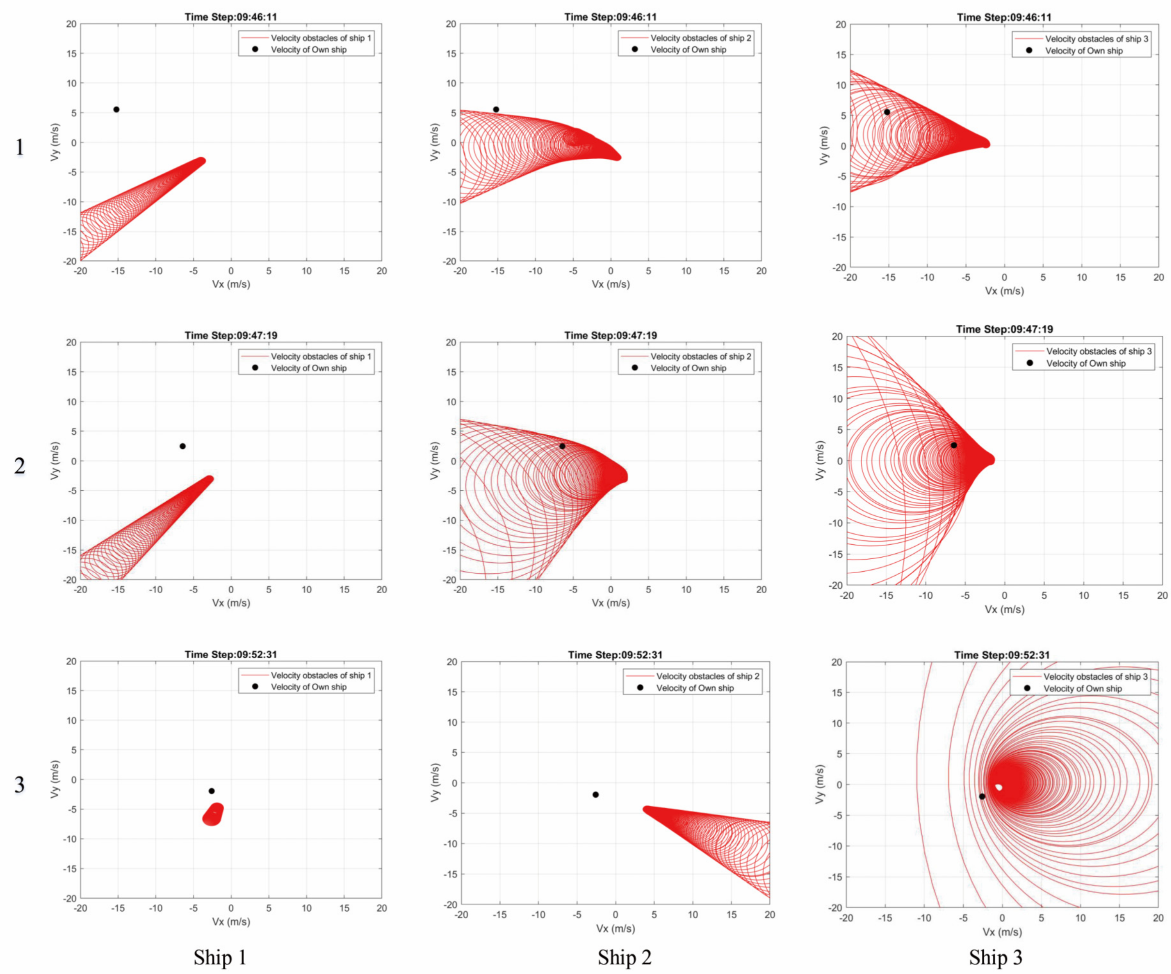


Figure 3.23 Examples of case 1 obtained with the previous TD-NLVO

One can notice in table 3.9 that the detection of the individual NLVOs is the same as results in table 3.3. This is reasonable because of the same NLVO approach utilised in the two algorithms. However, as indicated in table 3.9, the TD-NLVO is incapable of detecting the multiple ship encounter situation due to the decomposition process, as indicated in figure 8. Such a design also could lead to misinterpretation, e.g. in figure 3.23 ships 3 case, the figure shows that there is space outside the VO that the own ship is safe to choose. Actually, it is otherwise because one large VO is not included in the figure.

Based on the comparison between the previous TD-NLVO and the improved core algorithm, the advantage the improved method are as follows: 1) The encounter situation is considered as a whole in the form of combined NLVO(s). 2) For the combined NLVO(s), firstly the violation of NLVO, i.e. collision candidates, can be determined , secondly, with the individual NLVO of each target ship, the participant which contributes to such a violation, their duration in detection time and other information, e.g. ship name, ship particulars, etc. can be furtherly obtained.

However, there are also some disadvantages of the proposed algorithm: 1) Due to the union operation of individual VO induced by each data point of the target ship, the estimated duration of VO violation is no longer available in this new algorithm. 2) Due to the computational load on the Boolean operations, the time of calculation is increased to a certain extent. As for point 1), since the goal of the algorithm is to detect the collision candidates and multiple ship encounter situation, and such algorithm does not measure the actual distance between ships, the omission of this information is acceptable. As for point 2), the computational time can be improved with the trade-off between the accuracy on promoting the ConfP with points of polygon and optimization on the efficiency of the program, e.g. introducing a data compression algorithm such as Douglas-Peucker algorithm to accelerate the computation speed while maintaining the accuracy of the computation.

3.5.6 Detailed Analysis of the Union of NLVO Sets

For a ship having encounters with multiple target ships, each target ship will induce an individual NLVO at the detection time. Boolean operation among these individual NLVOs is performed to obtain the combined NLVO which can reflect the encounter situation in the velocity domain of the own ship. During this process, multiple scenarios could happen, which are illustrated in figure 3.24, respectively:

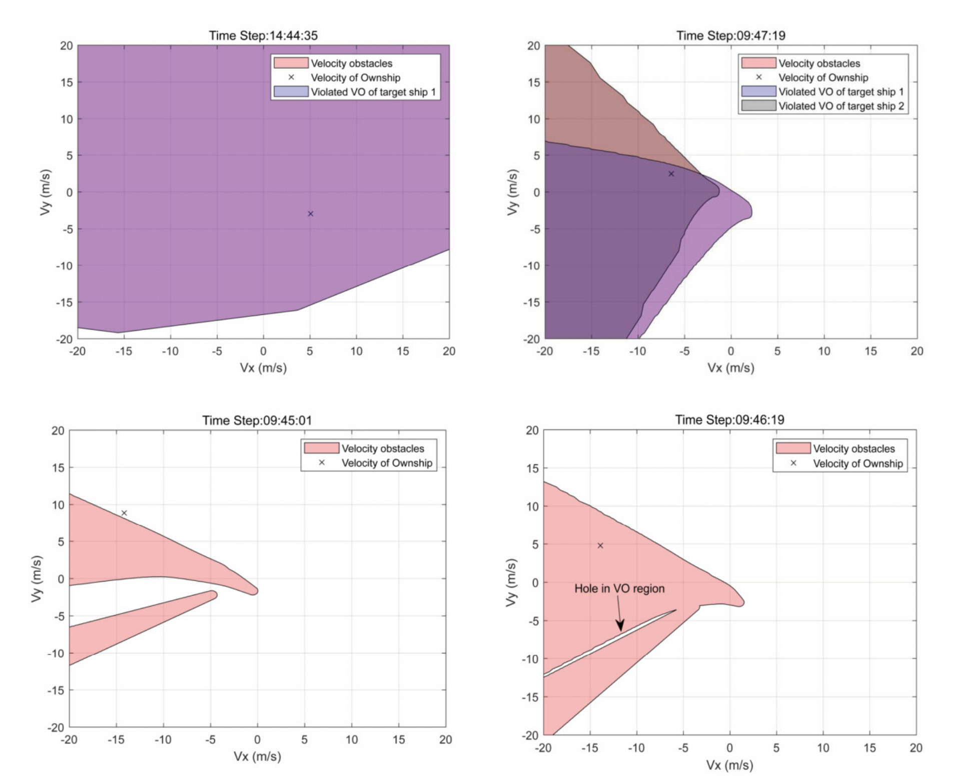


Figure 3.24 Example of four combined situations when performing the Boolean operation on individual NLVOs

Figure 3.24 illustrates the examples of four typical combined NLVOs which are detected by the algorithm: 1) One combined NLVO where the contour of it is the largest individual NLVO and other individual NLVOs are "absorbed" within; 2) One combined NLVO where the contour of it is the combination of certain individual NLVOs; 3) Multiple combined NLVO where individual NLVOs are combined into multiple groups, and 4) One combined NLVO where there is one or multiple "holes" inside. For scenario 1), 2) and 3) it is easy to determine if the velocity of own ship falls into the one of combined NLVO(s) or not, however, for scenario 4), it is otherwise. Due to the complicated situations when individual NLVOs overlapping with each other, in certain cases that within the combined NLVO, there will be certain regions where the velocity within the region are "safe" for the own ship to choose, i.e. if the velocity of own ship falls into the "hole" within the combined NLVO, the criterion of collision candidates will not be satisfied. Within the design of the algorithm, every polygon generated during the Boolean operation is stored separately. Therefore, there should be a method that can avoid potential false detection in this situation. We designed a criterion to avoid such false detection that only the situation where the velocity of the own ship falls into one of the combined polygons will be considered a violation of NLVO, i.e. for velocity of own ship that falls into the combined NLVO and the "hole" within at the same time, it will not be considered as a violation.

3.6 Conclusions

Identifying the dangerous encounter between ships and estimate the geometric probability of ship collision accident is the first and critical step for probabilistic collision risk analysis for ports and waterways.

In this chapter, a new collision candidate detection method based on Non-linear Velocity Obstacle algorithm is presented. Rather than determining a collision candidate via the Spatio-temporal relation between ships at certain time instances, in this chapter a collision candidate is defined as ship pairs in the process of encountering such that the velocity obstacle is violated by own ship during a certain period. A series of the case study is conducted to illustrate the efficacy of the proposed method on identifying the encounter between ships that satisfy the pre-set safety boundary, and comparison between existing methods that utilised indicators such as T/DCPA, etc. as criteria.

The comparisons indicate that the proposed method has high reliability with respect to the rerun of the method since it is a deterministic method and utilises historical AIS data. Sensitivity analysis on the influences of the two parameters scanning interval and linking threshold indicate that, compared to the well-known CPA-based method and six other detection methods, the new TD-NLVO method is less sensitive to the values of these parameters. Such characteristics can facilitate risk assessors avoiding the problem of choosing the proper parameters of the method.

Besides, a modified TD-NLVO has also been presented to identify the multi-ship encounter situation with historical AIS data, via the Boolean operation on polygons is introduced to combine the Non-Linear Velocity Obstacles (VOs). With such improvement, the multiple ship encounter situation can be considered as a whole, instead of decomposing such situation into multiple two-ship encounter scenarios.

With the improvement in this research, it provides a potential for new risk measurement of encounter situations where the coverage of the combined NLVO can be utilised as an indicator

(Huang and van Gelder, 2019). The proposed method provides a new perspective to analyse the ship encounters in the interesting waters. The results of the analysis can provide more detailed information to the relevant stakeholders to understand the collision risk in the region and facilitate the decision-making process of safety measures.

Chapter 4 Causation Probability Modelling

In this chapter, a novel method to model causation factors to consider the influence of encounter information in causation probability modelling is proposed. A credal probabilistic graphical network model based on imprecise probabilities was established based on accident investigation reports and domain experts as the overall framework to represent expert knowledge and probabilistic inference under uncertainty. Causation probability is estimated from the micro-to-macroscopic perspective where information of ship encounters are integrated into the causation model to perform probabilistic inference on each encounter and to obtain collective results. The causation probability interval is obtained and compared between the model with and without the availability of geometric encounter data. The results indicate that: 1) The encounter information (relative bearing, TCPA, and presence of other ship) has influence on causation probability of ship collision accident to certain extent; human and organisational factors play more significant role; and 2) With AIS data integration, causation probability analysis can be utilised to determine encounters with higher likelihood and obtain details of dangerous ship encounters in regional maritime traffic.

Acknowledgement: the content of this chapter is the edited version of the following paper:

Chen, P., Mou, J., & van Gelder, P. H. A. J. M. (2019). Integration of individual encounter information into causation probability modelling of ship collision accidents. *Safety Science*, 120, 636-651.

4.1 Introduction

The occurrence of collision accident is the results of multiple contributors, e.g. dangerous encounter situations, failure of the mechanical components, extreme weather conditions, etc. To obtain comprehensive insights on the risk of ship collision, analysing accident causations is an indispensable element.

Focusing on causation probability, various researches have been conducted, e.g. (Bye and Aalberg, 2018; Sotiralis et al., 2016; Valdez Banda et al., 2016a; Zhang et al., 2018a). Statistics analysis of historical accident data, tree-structured analysis modelling, Bayesian network modelling, etc. are well implemented to estimate the probability. A detailed literature review can be found in section 4.2. In practices, however, there are two issues among causation probability modelling:

1) The conflict between high demand for accident information, e.g. accident investigation report, etc. and scarceness of them in practices, which results in the uncertainty in the models.

2) The omission of the influence of traffic context information, e.g. AIS data in the research area when modelling causation probability, which results in a context-independent analysis.

For the first issue, causation probability modelling is a data demanding task, since it often requires detailed information on ships' behaviour, interactions between Officer On Watch (OOW), weather conditions, e.g. (Martins and Maturana, 2013). Such information heavily relies on the accident investigation report, on-site interviews, etc. However, due to the scarce nature of the accident occurrence and variety of level of details of the accident investigation report, the information from accident investigation report may be insufficient for comprehensive modelling of the probability (Hanninen, 2014). Under such situation, knowledge, and experience from experts in the field act as an important role, see (Friis-Hansen and Simonsen, 2002; Montewka et al., 2014; Trucco et al., 2008), etc. For the second issue, current probabilistic risk analysis model of collision accident often investigate the two elements separately, i.e. the geometric collision probability and causation probability are considered as mutually independent variables, where the influence of individual encounter situation, e.g. clearness of encounter type, etc. on the causation model are rarely considered when modelling causation probability. Since individual ships are the fundamental component of the maritime traffic system, such information will result in different estimates of causation probability for individuals encounters, it is therefore of great necessity to design new methods to integrate such information.

To overcome such issues and to further improve the causation modelling of ship collision accidents, this research proposes a new perspective of modelling inspired by conditional probability where the causation probability $P_{Causation}=P(Causation|Geometric)$ is estimated given the geometric encounter information, i.e. the influence of encounter situation, e.g. velocity, relative bearing, etc. are considered. The goal of this research is to extend the current models with additional encounter information that can be obtained from AIS data, and perform the causal inference considering the uncertainties in the knowledge elicitation process from the field experts. The causation probability of ship collision is estimated based on individual inference. The probability obtained following conditional probability can be integrated into the framework proposed by Fujii(Fujii and Shiobara, 1971) and Macduff(Macduff, 1974) to further improve the risk analysis framework by considering the encounter context information into the model. The maritime traffic system is a complex socio-technical system, and the individual ships are its fundamental components. By considering the causation probability of each dangerous encounter at the individual level, and estimating causation probability based on the weighted arithmetic expectation, the causation probability model for collision accidents can be more regional traffic dependent and comprehensive.

To do so, Credal Network, which can be considered as an extension of the Bayesian network that could treat epistemic uncertainty due to lack of data using interval analysis (Zhang et al., 2018a), is introduced as the main tool for causation probability modelling. Expert knowledge is extracted to build the qualitative and quantitative of the network. Additional input variables of encounter situation are included in the network and information of them are extracted from historical AIS data as additional inputs. Individual probabilistic inference for each encounter cases is then conducted, which composites the results of the model. Ultimately, a comparison between the model without encounter situation variables, the model with input variables but no input data, and model with integrated results of individual encounters are conducted to analyse the influence of the method.

4.2 Existing Methods

To investigate the causality of ship collision accident and to estimate the probability of collision due to such influence, many scholars have conducted research following various approaches. Accident statistical analysis, as one of the most fundamental approach, is widely applied in probabilistic risk analysis for collision accident.

With the development of reliability engineering technology and the understanding of accident causality, Fault Tree Analysis (FTA) and Event Tree (ET) analysis have drawn attention from both the academia and industry. By systematically investigating the contributing factors of the accident and their causation relationships, a hierarchical, tree-structured conceptual model can be established. The probability of collision accident can be obtained based on the propagation of the probability of initial events within the model using Boolean logic. Due to the concise structure of the model, such methods have been widely applied in related works: Based on the accident investigation report, Macrae (Macrae, 2009) identified the common pattern of human factor-induced errors in collision and grounding accident and established the generalized accident scenarios based on event tree. Martins and Maturana (Martins and Maturana, 2010) conducted extensive quantitative analysis on the influence of human errors in collision and grounding of oil tankers. A comprehensive Fault Tree model was established to estimate the probability of the accident. Similar work can also be found in (Uğurlu et al., 2013). The advantage of such an approach is the concise structure of the model and high efficiency when modelling. However, the conflict between high demand for detailed records which can reflect human and organisational behaviours, externals factors such as weather conditions, etc. between scarceness of data still hindered the performance of the methods. Besides, the nature of Boolean logic is often criticised for incapable of reflecting the multiple states of contributing factors, e.g. (Montewka et al., 2014), which limits the efficacy of the Tree-structured modelling to estimate the probability.

To improve the deficiencies of tree structure analysis models, more system engineering analysis methods are introduced, among which Bayesian networks (Langseth and Portinale, 2007) are the most representative tool utilised in ship collision risk modelling, e.g. (Ren et al., 2008). Combining Fault Tree and Bayesian network, Trucco, et al. (Trucco et al., 2006) conducted quantitative analysis on the influence of human and organisational factors on ship collision accidents. Hanninen and Kujala (Hanninen and Kujala, 2012; Hänninen and Kujala, 2009) conducted series of research on collision and grounding risk in the Gulf of Finland with the Bayesian network to model causation probability and analysed influence of accident contributing factors. Similar work can also be seen in (Zhang et al., 2013). Montweka et al. (Montewka et al., 2014) proposed a comprehensive risk analysis framework for collision risk analysis of Ropax vessel, within which various sources of inputs are introduced to obtain the probability of various accident severities. With the growing attention on the influence of human and organisational factors in collision risk, theories such as HFACS are introduced to obtain the clear structure of the model, e.g. (Martins and Maturana, 2013; Morel and Chauvin, 2006; Sotiralis et al., 2016). Compared with statistical analysis and tree-structured analysis tools, the advantages of Bayesian networks lie in several aspects: 1) More flexibility in modelling accident contributing factors. Accident contributing factors in Bayesian networks can have multiple states or following certain probability distribution functions. Their causation relationships are also defined according to the CPT instead of Boolean logic, which give the model more flexibility in complex system modelling; 2) Capability of data infusion. The inputs for the Bayesian network can have multiple sources, e.g. expert knowledge, historical accident statistics, etc. Such capability gives the investigators the opportunity to take full advantage of the resources.

In conclusion, based on the review on existing works on causation probability modelling for ship collision accident, there are two issues that should be improved: 1) Causation modelling from a macroscopic perspective while omitting the influence of individual encounter information on the results, and 2) Uncertainty of the results due to possible limited and incomplete information of accident.

For these issues, two aspects could explain: 1) Quantitative risk analysis for ship collision accident is usually performed from a macroscopic perspective, i.e. it usually analyses the risk within certain areas, e.g. port areas and waterways. The process of risk modelling for such purpose usually is conducted in a manner that obtains information from accident investigation reports and, possible field experts to determine the structure and parameter setting of the model, the results of which reflect the group consensus towards the accident. However, as a critical component of the maritime traffic system, the influence of encounter situation on individual ships would lead to the different likelihood of the accident, i.e. the results of the causation model can be case-dependent. Then the problem would be how to estimate the causation probability of ship collision accident within a certain region considering the contribution of individual encounter information. 2) When performing causation modelling, due to the scarceness nature of the accident, the accident investigation report or another form of data that contains detailed information about how an accident occurs is often insufficient to construct the comprehensive structure of the model and determine the parameter settings. To tackle such problem, field experts are considered important sources of data. Although many methods have been proposed for the expert elicitation process (Zhang and Thai, 2016), the results obtained could be vague, imprecise, and difficult to be properly interpreted, hence introduced additional uncertainty into the model.

In this chapter, the causation probability from a macroscopic perspective is estimated based on the results of the individual encounters with information obtained from AIS data (Chen et al., 2018). Accident investigation reports and knowledge from field experts are utilised to establish the causation model for the task using the Credal network. By doing so, individual encounters will be assessed with the causation model and together formulate the result to reflect the causation probability for collision in a certain region.

4.3 Proposed Methodology

4.3.1 Methodological Overview of Integral Causation Modelling

The maritime transport system is a complex system where individual ships are the fundamental elements of it. The causation probability of collision accident for certain areas is estimated via performing probabilistic inference on individual cases based on the Credal Network-based causation modelling and then combine them as causation probability of collision in macroscopic perspective. The goal of the chapter is to extend the causation probability modelling of ship collision accident with encounter situation information and perform probability inference with intervals that can reflect the uncertainties of knowledge elicitation processes of experts. The framework of the methods is indicated in figure 4.1:

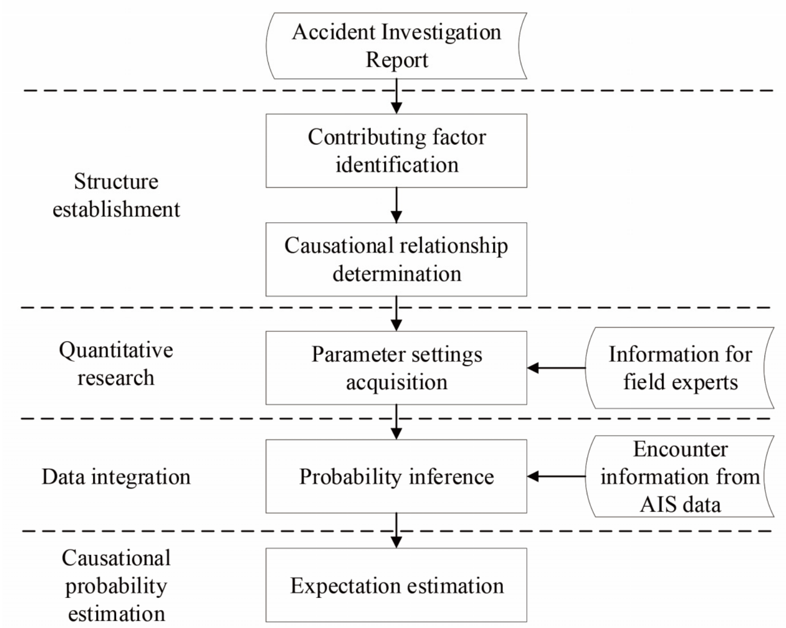


Figure 4.1 Framework of the proposed method

As the foundation of the method, Credal Network is introduced for probabilistic inference. The Structure, which is the qualitative part of the model, is established based on the accident investigation report collected from the marine casualties and incidents database of Global Integrated Shipping Information System (GISIS) of IMO. The accident contributing factors and their inter-relationships are identified following the HFACS-based taxonomy proposed by Chauvin et al. (Chauvin et al., 2013) utilising the detailed analysis in the reports. Knowledge from experts with experience as researchers and captains are elicited to determine the parameter settings of the network. After these two steps, information of individual encounter collected using the Time Discrete Non-linear Velocity Obstacle algorithm (Chen et al., 2018) will be utilised to perform probabilistic inference for each encounter. Based on the probabilistic inference, the causation probability of collision is estimated with a weighted average.

4.3.2 Credal Network

One aspect of Bayesian network modelling in risk analysis that is often criticised is the requirement for point estimates of the probability entries of the variables, which is sometimes difficult due to the limited and incomplete information (Hanninen, 2014). In practice, knowledge from field experts are an important source of information for collision risk modelling, however, on the one hand, such information can facilitate researchers to determine the probability entries, on the other hand, they are often expressed in a linguistic, imprecise manner. To improve such deficiency and perform probabilistic inference with impreciseness, Credal Network (Cozman, 2000) is then introduced. The credal network is an extension of Bayesian networks based on the concept of credal sets (Levi, 1980), where the probabilities of events in the network are determined as a convex set of probabilities, instead of point estimates, to reflect the uncertainty about the occurrence of these events. Compared with the traditional Bayesian network, one of the advantages of this approach is that it can perform probabilistic inference with imprecise values, e.g. probability intervals. Several algorithms are proposed to perform interval probabilistic inference within Credal Network, see (Antonucci et al., 2010; Fagiuoli and Zaffalon, 1998; Tolo et al., 2018). As for the applications of such methods in probabilistic risk analysis, Misuri et al. (Misuri et al., 2018) established a credal network model for security assessment of critical infrastructures by converting a Fault Tree-based model and compared it with the Dempster-Shafter theory to prove its applicability in imprecise probabilistic inference. Zhang et al. (Zhang et al., 2018a) analysed the risk of the maritime accident using the credal network and demonstrated the capability of the method on inference with expert knowledge. Besides, few works have been conducted in the related field.

The theory of Credal Network (CN) was proposed by Cozman (Cozman, 2000), which describes Credal network as a graphical model for the probabilistic inference that "*associate convex sets of probability* measures *with directed acyclic graphs*". With the utilisation of such a model, the probabilistic inference can be conducted with imprecise inputs. The component of CN contains two folds: 1) Directed acyclic graph, which graphically demonstrates the probabilistic relationships between variables, e.g. dependency and conditional independence, etc.; and 2) Credal set, which is a set of possible probabilities associated to each variable in the network, to express the impreciseness of the probability of the corresponding variable. For example, given a variable X and its probabilities $p_1(X), p_2(X), \cdots; p_i(X)$, its credal set can be denoted as $\mathrm{K}(\mathrm{X}) = (p_1(X), p_2(X), \cdots, p_i(X))$ that contains all the point probabilities.

From the definition, one can consider CN is an extension of the Bayesian network, as it shares the same principle and graphical structure. The difference, also the advantage of CN, is that it utilises sets of probability to express the imprecise information about the variables and the capability in performing probabilistic inference with such sets of probabilities. For the Bayesian network, the joint probability over a set of variables $\boldsymbol{X}$ is expressed in Eq. 4.1:

$$p(X) = \prod_i p\left(X_i \middle| pa(X_i)\right) \tag{1.9}$$

For CN, such inference can be conducted according to Eq. 4.2:

$$\left\{ P(\mathrm{X}): \mathrm{P}(\mathrm{x}) = \prod_{i=1}^{n} \mathrm{P}(x_i|\pi_i) \quad \forall \mathrm{x} \in \Omega_{\mathrm{x}}, \mathrm{P}(X_i|\pi_i) \in K(X_i|\pi_i) \quad \forall \pi_i \in \Omega_{\mathrm{x}} \right\} \tag{1.10}$$

Where Ω_{x} is the sample space, π_i is the evidence from Ω_{x}, $K(X_i|\pi_i)$ is the credal set given evidence π_i, $\mathrm{P}(X_i|\pi_i)$ is the conditional probability of variable X_i.

According to the definition of Credal set in (Cozman, 1999), for simply defined Credal set K of event A, which contains a finite set of the extreme value of probabilities. The probability interval for event A can be obtained according to Eq. 4.3:

$$\underline{P}(A) = \min_{P \in K} P(A), \quad \overline{P}(A) = \max_{P \in K} P(A) \tag{1.11}$$

Where A is the event interested. $\mathrm{P}(\mathrm{A})$ is the probability of event A in the credal set. $\underline{\mathrm{P}}(\mathrm{A})$ and $\overline{\mathrm{P}}(\mathrm{A})$ are the lower bound and upper bound of the probability of event A, given the corresponding credal set. The inference of the variable in the credal network is performed by applying conditional probability inference on each point in the creedal set to obtain the posterior probabilities. The posterior credal set is established with the union of these results. Hence, the posterior interval for a variable can be obtained by determining the minimum and maximum probability among this posterior credal set. From the process, one can see that the joint probabilistic inference in the credal network is conducted with multiple alternatives for the variables' probability input. It can be considered as the inclusion of multiple Bayesian networks with the same structure but different probability inputs.

Due to the multiple probability setting in the Credal Network, the exact inference of probabilities in the model is an NP-hard problem (Cozman, 2000), i.e. the exact inference cannot be performed in polynomial time. To solve this problem and take full advantage of the method, several approximate inference methods are proposed, among which the 2U algorithm (Fagiuoli and Zaffalon, 1998) is well applied. Antonucci et al. (Antonucci et al., 2010) then generalized the requirement in 2U to perform inference with Credal Network where variables have multiple states. In application, there are many software packages available, e.g. JavaBayes (Cozman, 2000), GL2U package (Antonucci et al., 2010), etc. We utilised JavaBayes as the basic tool in this chapter.

4.3.3 HFACS for Ship Collision Accident

With the development of accident investigation and modelling, Human and Organizational Factors (HOF) are well-acknowledged as one of the major contributors. To systematically analyse the causations of accidents, many methods were proposed, among which HFACS has drawn much attention from academia and industry, due to its characteristics in its taxonomic nature and the reliability of classification of accident contributors among different evaluators (Salmon et al., 2012).

Shappell and Wiegmann (Shappell and Wiegmann, 2000) firstly proposed the method as the systematic tool for HOF failures analysis in aviation accidents. According to the definition, HOF failures are classified into four different levels: 1) Unsafe acts; 2) Preconditions for unsafe acts; 3) Unsafe supervision, and 4) Organisational influences. Such classification system has been widely applied as a taxonomy for accident statistics analysis and causation modelling in many domains, e.g. (Soner et al., 2015; Yıldırım et al., 2019; Zhang et al., 2019b) etc. Chauvin et al. (Chauvin et al., 2013) extended the system with an additional level of external factors that contains regulatory factors into the system and proposed HFACS-Coll as the taxonomy to analyse ship collision accident. Such a system is introduced as the basic taxonomy, which is shown in Table 4.1.

Table 4.1 Contents of HFACS-Coll (Chauvin et al., 2013)

Unsafe acts	Errors	Skill-based errors Decision errors Perceptual errors
	Violations	Routine Exceptional
Preconditions for Unsafe Acts	Environmental factors	Physical environment Technological environment
	Condition of operators	Adverse mental state Adverse physiological state Physical/Mental limitations
	Personnel Factors	SRM (Communication/ BRM) Personal readiness
Unsafe leadership		Inadequate leadership Planned inappropriate operation Failed to correct the problem Leadership violations
Organizational influences		Resource management Organizational climate Organizational process
Outside factors		Regulatory factors Other

4.4 Causation Modelling

This section illustrates the detailed procedure to establish the causation model for ship collision accident based on HFACS and CN, which are as follows: 1) Contributing factor identification; 2) Qualitative modelling; 3) Quantitative modelling, and 4) Probabilistic inference.

4.4.1 Collision Investigation Report

GISIS is a data platform proposed and enforced by IMO to collect and share the maritime information of their member states. The archive of marine casualties and incidents contains all the accident investigation reports adopted by the maritime safety authorities. To build the causation inference model, 20 accident reports from 1990 to mid-2018, which concerns at least two merchant ships collisions or collision between a merchant ship and fishing vessel are collected and reviewed in detail. The regions where the accidents happened were at open sea, main channels, and port areas, etc. We have noticed the possible influence of the region on the navigation system of ships, however, due to the scarce number of accidents, the number of accident reports may be insufficient to establish the model if the region is specified. We have included all the cases recorded in the reports to build a general model. Nevertheless, to implement risk analysis in a specific region, the regional factors and its influence on the model should be acknowledged and considered during the modelling process.

4.4.2 Accident Contributing Factors

According to HFACS-Coll model, contributing factors of ship collision accident are grouped into five categories, each of which are the prerequisites of one another, e.g. "Unsafe acts" is the obvious, easy to detect errors and violations during the failed collision avoidance, while "Preconditions of unsafe acts" describes the conditions and practices of ship officers that could cause unsafe acts. Through such logic of analysis, factors that occurred during the accidents can be analysed from a systematic and comprehensive manner.

Accident investigation reports contain detailed chronological records about what happened when the collision occurred, e.g. intra- and inter-ship communication details, collision avoidance maneuverers, etc. Taking the report on the collision between Greek bulk carrier "Heraklia" and Chinese bulk carrier "Anping6" at 1035-hour, 15th May 2004 as an example, the course of the accident is shown in Table 4.2:

Table 4.2 The course of collision accident between "Heraklia" and "AnPing6"

Timeline	Actions of AnPing6	Actions of Heraklia
0940		Pilot boarded
0953	Heaved up anchor for departing for inbound	Singled up, then all lines letting go at 0955; Unberthed with 3 tugs assistance;
1010	Anchor cleared the sea bottom; Anchor ball lowered down; Departing from Anchorage	Passed breakwater at 1013; Departing for outbound through main channel 130; Pilot disembarked at 1015; Pilot failed to inform captain the traffic information of main channel 130 ahead
1025	Heraklia detected; Relative distance: 2.5 nm; Speed: 10.5 kn; Course altered due to another vessel	-
1028	Called outbound vessel in main channel 130 on VHF 08 in Chinese; Proceed with full ahead without any response from Heraklia	-

1032	-	Called Anping6 by English on VHF 16; Full speed ahead without respond from Anping6
1033	Stopped and reversed her engine to avoid the collision	-
1034	Collision occurred	

From the course of accident, one can find the following factors contributed to the occurrence of collision: 1) Failure to keep proper lookout during navigation: neither of the ships identifies each other in an ample time; 2) Failure of communication: Anping6 contact "Heraklia" in Chinese on VHF channel 08, which is the wrong action since the proper action should be calling counterpart in English on VHF channel 16; 3) Failed duty of pilot: the pilot failed his duty to inform the captain of the traffic in the main channel; 4) Failed to use proper speed under situation; 5) Misinterpretation and assessment of encounter situation: neither of the ships correctly assess the encounter situation and perform corresponding avoidance manoeuvres; 6) Failure of effectively use Aids to Navigations (e.g. radar, AIS, etc.). Each of these factors can be classified into the corresponding category based on HFACS-Coll, e.g. Failure of communication and effective lookout is an explicit violation of rules, which belongs to unsafe acts, while factors such as failure to effectively utilise aids to navigations belong to preconditions of the unsafe acts, which could result in the occurrence of unsafe acts.

To obtain the contributing factors of a ship collision accident, each report was reviewed carefully, especially the contents concerning the course of the accident, to identify factors explicitly mentioned and extract them as the basic information. The List of accident reports reviewed is shown in Appendix III. It should be noted that although HFACS require investigators to analyse accident based on the four aspects, since in original reports it is rare to see the accident investigators explicitly mentioned supervision and organisational factors in the reports, in this process, the management factors are not included. Based on the review process, the following factors are identified and collected:

Table 4.3 Contributing factors for ship collision accidents

Contributing factors
Communication (Both intra- and inter-ship); Lookout; Competency of crew; Assessment of situation; Failure to use Aids to Navigations (AIS, radar, etc.); Visibility; Wrong perception; Violation of regulations; Failure of avoidance measures; Failure of duty; Fatigue; Confidence; Light and sound signals; Encounter situations; Mechanical failures; Extreme external factors;

4.4.3 Structure of Credal Network

In this step, the causation relationships between contributing factors, as well as the structure of the network, are determined.

It is well acknowledged that the collision avoidance performance during critical encounter is usually composed of three phases, e.g. (Montewka et al., 2017): 1) Detection, which implies that ship successfully detect the target ship that has collision risk with herself; 2) Assessment, which implies OOW evaluate the encounter situation and propose corresponding avoidance solutions; and 3) Execution, which denotes the process that OOW and ship crew perform the collision avoidance solution into effect. During each phase, a series of factors could result in the failure of the phase; hence the occurrence of the accident, e.g. for the detection phase, the failure of the lookout for a target ship could result in the collision between the own ship and the target ship, and the fatigue of OOWs and the poor visibility of the environment could lead to the failure of lookout by OOWs, i.e. for each phase of collision avoidance, the accident contributing factors can be analysed following the HFACS-Coll model. To analyse the accident contributing factors in a structured manner and to obtain a comprehensive structure of the credal network that can reflect the decision process and the structural analysis of the factors, for each phase of the collision avoidance performance, the HFACS-Coll is followed to analyse the causes identified from the investigation reports following the categories in the HFACS-Coll model. Following this way of thinking, the causation relationships between contributing factors are analysed with the analysis matrix (figure 4.2) from two different dimensions: 1) Process of collision avoidance, and 2) HFACS-Coll. It is worth mentioning that some variables, e.g. "Communication", "Competency" are the ones that could affect the behaviour of OOW at every phase of collision avoidance. For these variables, we define them as Global influence factors.

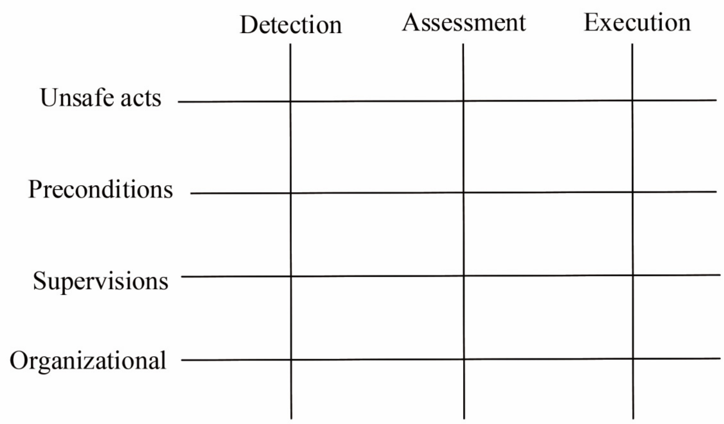


Figure 4.2 Analytical structure of the causation model

There are generally three ways to establish the structure of the network: 1) Data-driven approach, which is to extract causalities between variables statistically from accident data; 2) Expert knowledge elicitation, which is to determine the relationships according to the knowledge from field experts; and 3) Combination of both. Since ship collision is the accident with high impact but the low frequency, it is difficult to perform data mining to establish the structure. Existed literature and expert knowledge are utilised to facilitate the process, e.g. Some researchers have proposed that graphical model could be translated from classical models such as Fault Tree and Event Tree (Khakzad et al., 2011; Montewka et al., 2014). However, with such translation, the assumptions such as Boolean logical causations between variables constrain the efficacy of the model to some extent.

The relationships between the contributing factors are determined based on the chronological record of accident details based on the model matrix. The occurrence of ship collision is considered as the coupled results from the three main components: Detection, Assessment and Execution. Based on the process, the structure of the credal network without and with variables of encounter situation is determined as figure 4.3, and 4.4 indicate. Due to the limited accident investigation reports and the lack of causes identified in the reports, the organisational factors are limited in the model.

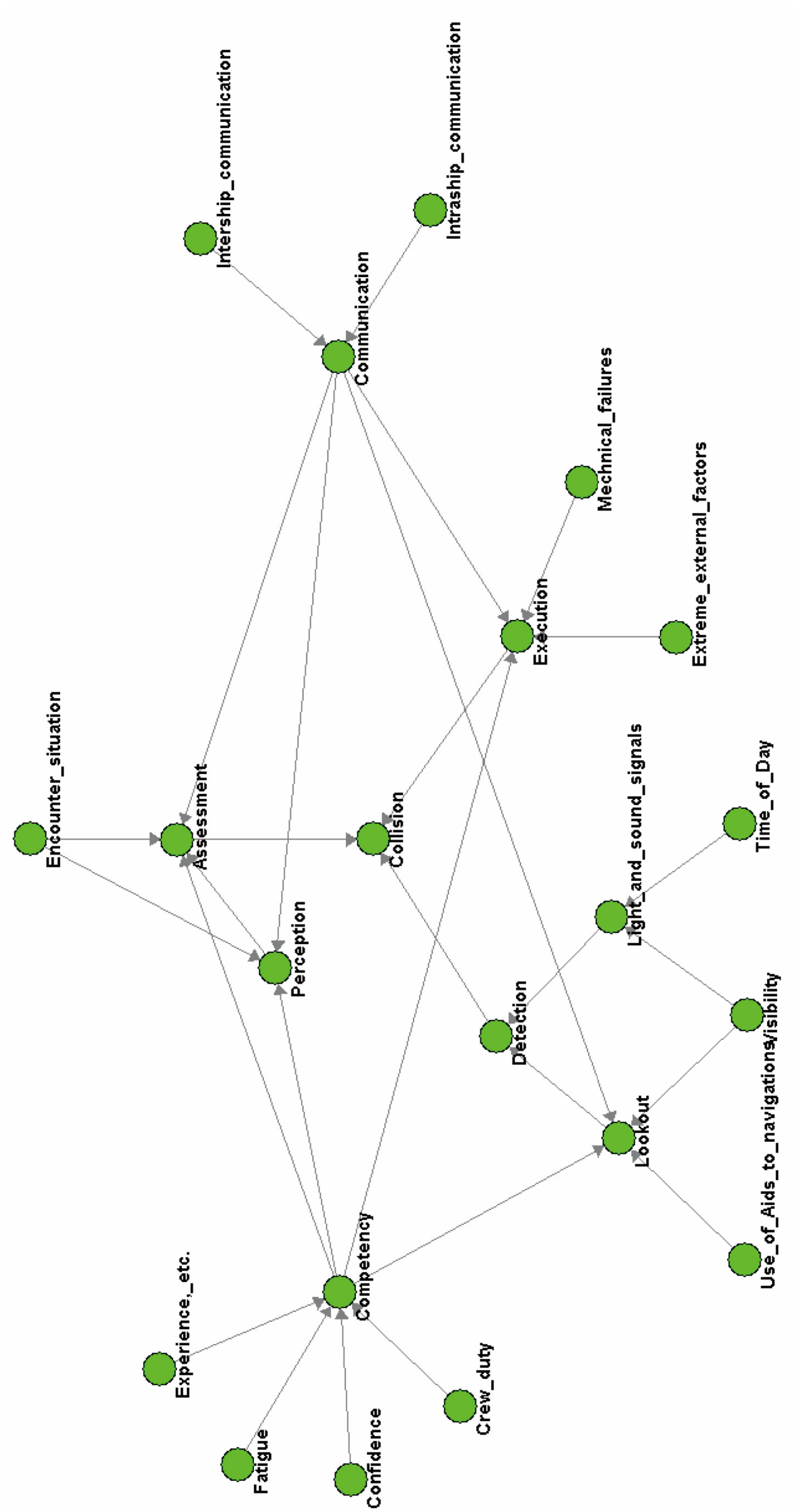


Figure 4.3 Structure of the causation probability model without AIS data

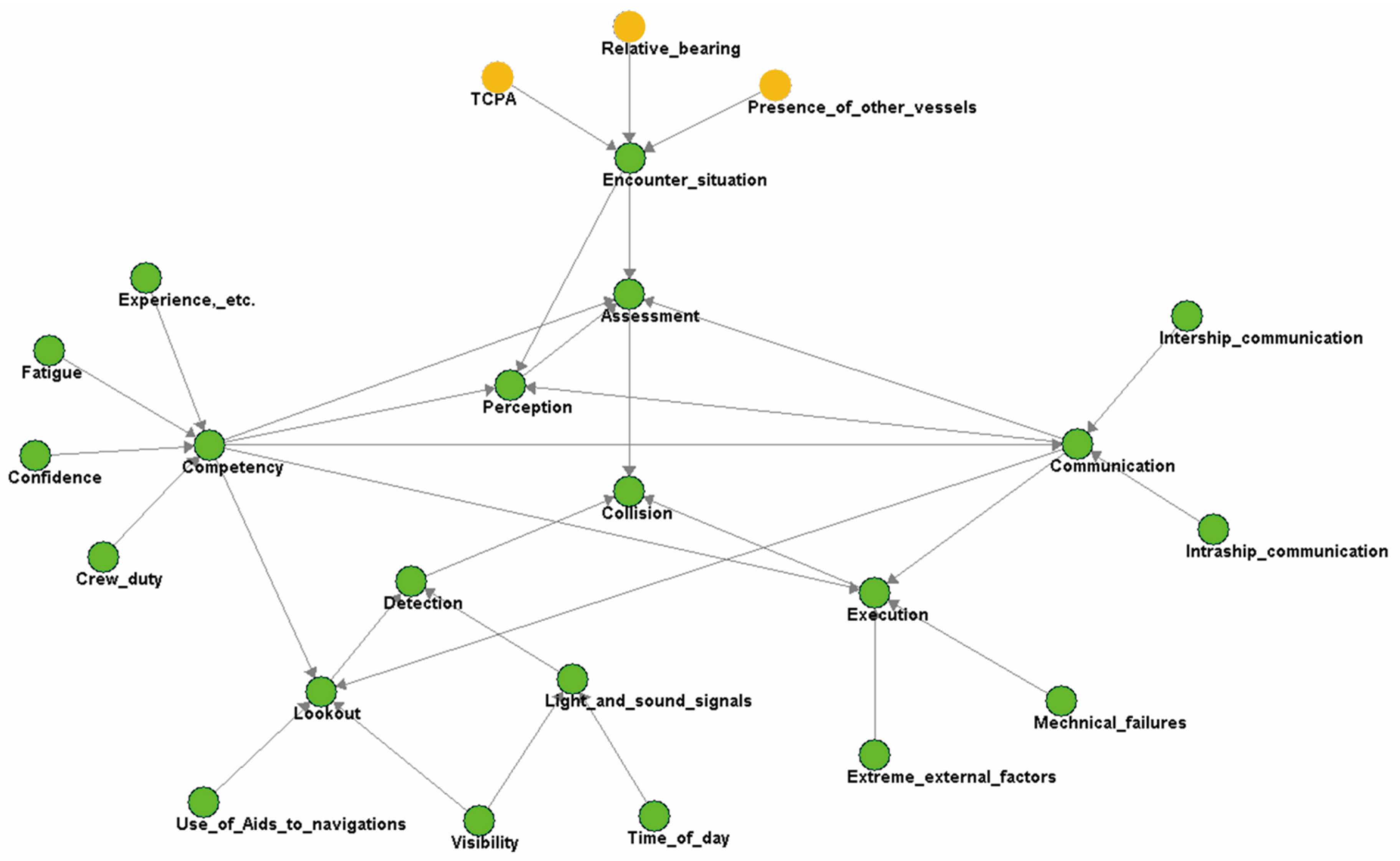


Figure 4.4 Structure of the causation probability model with AIS data (in yellow colour

4.4.4 Parameter Settings and Expert Elicitation

Probability parameter is another critical component of the graphical model. It quantifies the causation relationships between states of variables and offers quantitative results of the inference to decision-makers. In a Bayesian network, such parameters are usually given in the Conditional Probability Table (CPT) in the form of point estimation, either a crisp value or based on certain probabilistic distribution. With the limited data as input, however, such manner often induces additional uncertainty and the reliability of the model is often criticized. Besides, the number of probabilities entries also grow exponentially with the increment of the model's complexity, which makes it difficult to determine when more variables are considered. In a credal network, such deficiency can be alleviated by utilising interval estimations of probability and performing probabilistic inference with it.

The methods to determine the parameters are similar to structure modelling. In practices due to the limited data, knowledge from field experts is a valuable asset that can facilitate the work (Hanninen, 2014; Zhang and Thai, 2016). In this chapter, therefore, we also introduce an expert elicitation process to extract the necessary information. A similar questionnaire and expert elicitation process to work by Zhang et al. (Zhang et al., 2018a) to extract the information from 10 field experts are implemented in this work. An example of a questionnaire can be found in Appendix IV. The experts are required to provide their occupations and working experiences and make proper choices about the likelihood of the designed scenarios based on their own experiences. The composition and background information about the experts are shown as follows:

Expert 1: Full Professor in maritime transport safety and risk research, with 15 years of working experience and 2 years of working experience onboard ship.

Expert 2: Associate Professor in maritime transport safety and risk research, with 20 years of working experience as a captain on ocean-going ships and valid certificate.

Expert 3: Pilot with 7 years of working experience and a valid certificate.

Expert 4: Chief Officer with 7 years of working experience and a valid certificate.

Expert 5: Chief Officer with 7 years of working experience and a valid certificate.

Expert 6: Second Officer with 8 years of working experience and a valid certificate.

Expert 7: Captain, with 2 years of working experience and a valid certificate.

Expert 8: Captain, with 12 years of working experience and a valid certificate.

Expert 9: Captain, with 15 years of working experience and a valid certificate.

Expert 10: Captain, with 20 years of working experience and a valid certificate.

Combining the results from the experts with the method in (Zhang et al., 2018a), the probability intervals for the credal network are obtained as the prior inputs, e.g. the probability interval for successful detection are shown in table 4.4:

Table 4.4 Combined prior probability intervals of correct execution under different scenarios

Competency	External factors	Mechanical failure	Communication	Lowerbound	Upperbound
Adequate	TRUE	TRUE	Effective	0.97200	0.99800
			Ineffective	0.69375	0.89500
		FALSE	Effective	0.65431	0.86330
			Ineffective	0.38865	0.67180
	FALSE	TRUE	Effective	0.67908	0.89762
			Ineffective	0.31562	0.61987
		FALSE	Effective	0.31485	0.55576
			Ineffective	0.06564	0.23774
Inadequate	TRUE	TRUE	Effective	0.53542	0.79399
			Ineffective	0.21500	0.49500
		FALSE	Effective	0.15830	0.38791
			Ineffective	0.04654	0.18135
	FALSE	TRUE	Effective	0.15679	0.40248
			Ineffective	0.00900	0.09100
		FALSE	Effective	0.01674	0.10557
			Ineffective	0.00075	0.01679

4.5 Case study

In this section, a case study to demonstrate the efficacy of the proposed method is conducted. The water area of port Aarhus, Denmark, is chosen as the study object. The prior probabilistic results of Credal Network based on expert knowledge, results of collision candidate detection, and posterior probabilistic intervals of causation model are presented, respectively.

4.5.1 General Posterior Probability without AIS Data

Based on the information collected from accident investigation reports and field experts, a credal network model for causation factors of collision is established in the previous section. To conduct inference and obtain the posterior probability for each variable in the model, there are several software packages that can be utilised, e.g. JavaBayes (Cozman, 2000), GL2U (Antonucci et al., 2010), etc. Misuri et al. (Misuri et al., 2018) conducted a comparison of the performance between the two software and found out that GL2U may lead to the inconsistent result of certain variables if they are connected with Boolean gates. Therefore, in this chapter, we introduced the JavaBayes package for the task. The results of posterior probabilities are illustrated in Table 4.5:

Table 4.5 Posteriori probabilities of the credal network without input from AIS data

Variable	State	Probability Interval	Variable	State	Probability Interval
Collision	TRUE	[0.0429, 0.5044]	Inter-ship communication	Good	[0.82772, 0.96116]
	FALSE	[0.4956, 0.9571]		Bad	[0.03884, 0.17228]
Detection	Effective	[0.44881, 0.87922]	Communication	Effective	[0.77164, 0.97046]
	Ineffective	[0.12078, 0.55119]		Ineffective	[0.02954, 0.22835]
Assessment	Correct	[0.41978, 0.88421]	TCPA	Imminent	0.5
	Incorrect	[0.11579, 0.58022]		Non-imminent	0.5
Execution	Effective	[0.54374, 0.95]	Relative Bearing	Clear	0.5
	Ineffective	[0.05, 0.45626]		Unclear	0.5
Lookout	Effective	[0.46948, 0.91122]	Presence of other vessels	TRUE	0.5
	Ineffective	[0.08878, 0.53052]		FALSE	0.5
Light and Sound signals	TRUE	[0.49353, 0.72169]	Encounter situation	Clear	[0.38865, 0.57731]
	FALSE	[0.27831, 0.50647]		Unclear	[0.42269, 0.61135]
Use of Aids to navigation	Proper	[0.74166, 0.91918]	Experience	Sufficient	[0.71867, 0.90947]
	Improper	[0.08082. 0.25834]		Insufficient	[0.09053, 0.28133]
Visibility	Good	[0.61209, 0.84170]	Fatigue	TRUE	[0.51593, 0.78109]
	Bad	[0.15830, 0.38791]		FALSE	[0.21891, 0.48407]
Time of day	Day	0.5	Confidence	Proper	[0.64261, 0.87869]
	Night	0.5		Improper	[0.12131, 0.35739]
Extreme external factors	TRUE	[0.9, 0.99]	Crew duty	TRUE	[0.74132, 0.92212]
	FALSE	[0.01, 0.1]		FALSE	[0.07788, 0.25868]
Mechanical failures	TRUE	[0.69484, 0.88504]	Competency	Adequate	[0.46923, 0.88522]
	FALSE	[0.11496, 0.30516]		Inadequate	[0.11478, 0.53077]
Intra-ship communication	Good	[0.90473, 0.98914]	Perception	Correct	[0.54169, 0.89727]
	Bad	[0.01086, 0.09527]		Incorrect	[0.10273, 0.45831]

According to table 4.5, the probability of collision for a collision candidate falls into [0.0429, 0.5044]. It is evident that overall the probability of collision is smaller than non-collision, which indicates that the combined knowledge from expert tends to consider collision is unlikely to happen, considering the variables in the network and their causal relations. In the meantime, the range of each probability interval is also very large. Such phenomenon could be explained in two aspects: 1) The introduction of linguistic terms in the questionnaire (Zhang et al., 2018a), and 2) Incompleteness of the variable considered in the model. For the first aspect, we think it is reasonable to let the expert express their ambiguity toward the designed scenario in the model. As for the second aspect, we think with additional inputs from more field experts, and such uncertainty could be alleviated to some extent.

4.5.2 Results of Collision Candidate Detection

According to "Statistics Denmark"-the central authority on Danish statistics, the port of Aarhus is the second largest port in Denmark considering cargo throughput and largest container port, where maritime traffic is very active. To obtain the information of dangerous ship encounters in the area, one month (1st -31st Oct. 2018) of AIS data are collected from the open-access database of the Danish Maritime Authority as the dataset to identify collision candidates.

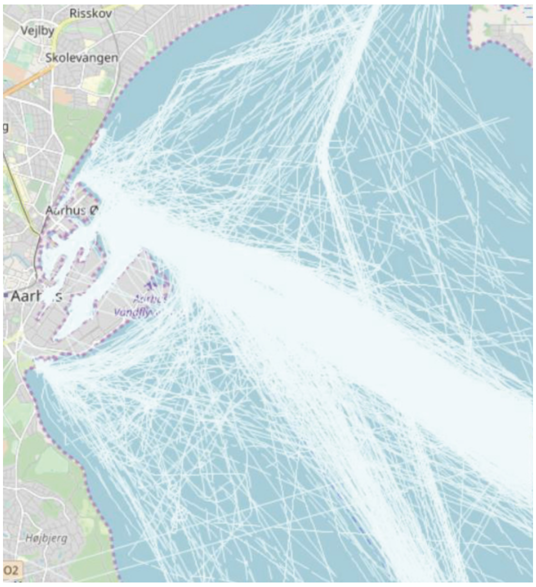


Figure 4.5 AIS trajectory in water areas of port Aarhus (1st -31st Oct. 2018)

Figure 4.5 illustrates the AIS trajectories in the research area in October 2018. As can be seen from the figure, there are two major shipping lanes originated from the port harbour of Aarhus and one spreading outside of the port in the area, various intersections of the trajectories indicates that the number of ship encounters could be very high in this area. The previous work of the authors (Chen et al., 2018) is introduced to obtain the number of collision candidates. For simplification, the parameters remain the same as in their previous work in which 1,000 meters is set as a criterion for collision candidate selection. However, more practical, accurate criteria can be further included. Since the pilot boat and tugs are frequently encountered with other ships during work, such types of ships are excluded from the datasets.

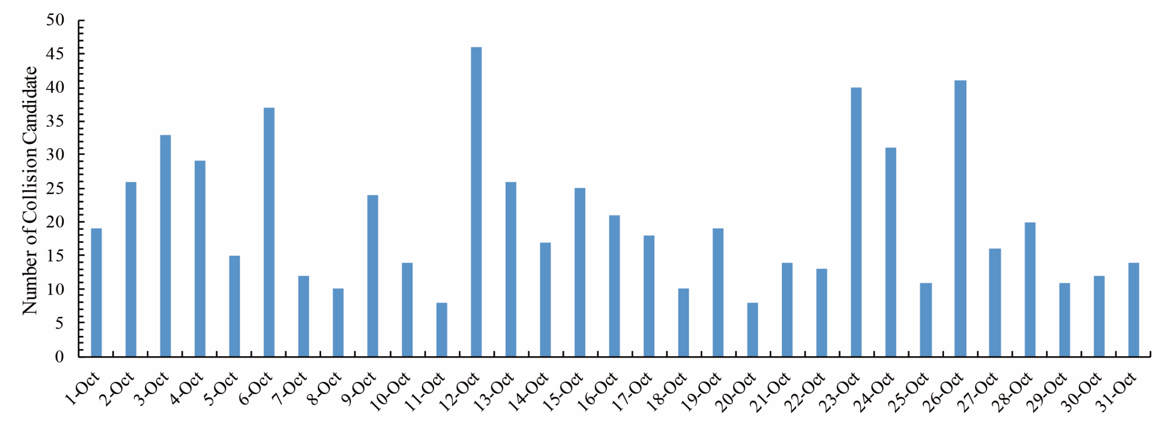


Figure 4.6 Daily distribution of the number of collision candidates

The results of collision candidate detection are shown in figure 4.6. In total, 640 cases of collision candidates are obtained using the algorithm in (Chen et al., 2018). It is obvious to see that such results share a periodical fluctuation within the timespan. This is consistent with the trend of traffic flow in the area. For OOW onboard, the encounter situation information, e.g. relative bearing, etc. are of critical importance to correctly assess and determine the encounter situation, hence conduct proper collision avoidance manoeuvre for safe passage. For example, if the relative bearing of two ships falls at the boundaries which are regulated by COLREGs to determine encounter type, it would be difficult for OOW the clearly determine the corresponding situation. Since the collision candidates are obtained in perspective from encounter process, the information of the encounter, e.g. TCPA, Relative bearing, and the chance of the presence of other ships when encounter evolves can be easily obtained with the integration of the results and ship AIS data. Such information is obtained as table 4.6 indicates to be utilised as input to the modified causation probability model.

Table 4.6 Illustration of encounter information obtained from AIS data

Ship 1	219XXX000
Ship 2	220XXX000
Detection Time	6:40:53 to 6:46:13
Duration of a dangerous encounter	6:42:51 to 6:48:22
TCPA (s)	175
DCPA (m)	405.9
Relative bearing 1 (°)	329.2
Relative bearing 2 (°)	11.1
Encounter situation clearness	Clear

4.5.3 Estimation of Posterior Probabilistic Results with AIS Data

Ship individuals are critical components of the maritime transport system, the information of encounter situation is one of the essential aspects which can influence the decision-making process of collision risk analysis and avoidance manoeuvring. However, the situation of each encounter may vary from one another, which results in various scenarios of collision risk analysis and decision-making for the OOW on board. As for modelling of the causation probability of ship collision, concerning the individual perspective, it is therefore of great necessity to integrate the encounter information into the model and quantify their influence.

Out of such perspective, the original Credal Network for ship collision is modified with three additional variables: “TCPA”, “Relative bearing”, and “Presence of others vessels”. As for TCPA, the threshold for TCPA to be imminent for collision avoidance is determined according to (He et al., 2017) to set as 20 mins, which is based on the experience of Captains. The presence of other vessel assumes that the encounter would be more complicated if there are other ships nearby, which could make OOW onboard difficult to determine the situation. As for the “relative bearing” variable, according to COLREGs, encounter situation is classified into “Head-on”, “Crossing”, and “Overtaking” three categories according to the relative bearings of both ships to each other. When the relative bearing of two ships falls into certain ranges, it would be difficult for OOW to determine the situation correctly. In this chapter, the range is set to be 1 degree around the boundaries of encounter categories.

With the analysis of AIS data in Section 4.5.2, 640 cases of encounter where the safety diameter of 1,000 meters is violated during the collision avoidance process are extracted from AIS data. The information of each record was coded into the network file of the causation model for inference, with the input of variables “TCPA”, “Relative bearing”, “Presence of other vessels”, and “Time of Day”. The evidence model is shown in Figure 4.7

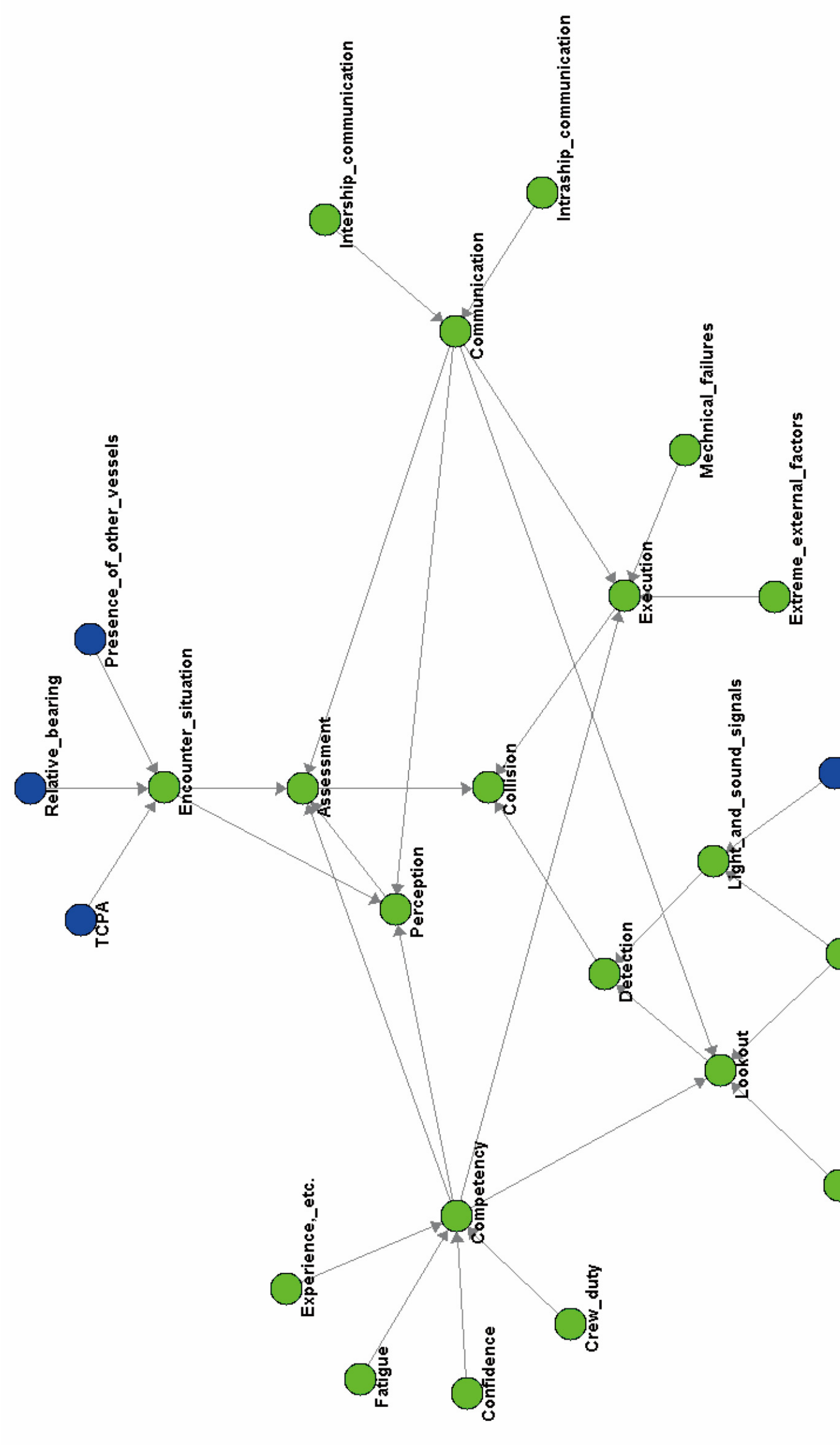


Figure 4.7 Illustration of probabilistic inference in the credal network

As shown in figure 4.7, the blue dot denotes the variables with evidence set, and a green dot represents variables without the input of evidence. For each encounter case, the causation probability of collision is obtained by performing probabilistic inference using JavaBayes package with the probability entries obtained in section 4.4.4, given the encounter information as input to the corresponding variables. Based on the data, 640 sets of probability intervals are estimated. Such results can be categorised into 13 different scenarios, which are shown in table 4.7 and 4.8, respectively:

Table 4.7 Results of inference on the probability of Collision

Category	Lower bound	Upper bound	Share (%)
1	0.02311	0.4241	0.3
2	0.02721	0.44091	0.5
3	0.02543	0.44103	20.0
4	0.0296	0.45769	55.2
5	0.03361	0.48455	0.2
6	0.03804	0.50084	0.8
7	0.03962	0.50645	3.6
8	0.04423	0.52256	13.4
9	0.04906	0.52929	1.1
10	0.05522	0.54085	0.2
11	0.05397	0.5452	2.8
12	0.06142	0.54793	0.2
13	0.06672	0.56369	1.9

Table 4.8 Results of inference of probability of no collision

Category	Lower bound	Upper bound	Share (%)
1	0.5759	0.97689	0.3
2	0.55909	0.97279	0.5
3	0.55897	0.97457	20
4	0.54231	0.9704	55.2
5	0.51545	0.96639	0.2
6	0.49916	0.96196	0.8
7	0.49355	0.96038	3.6
8	0.47744	0.95577	13.4
9	0.47071	0.95094	1.1
10	0.45915	0.94478	0.2
11	0.4548	0.94603	2.8
12	0.45207	0.93858	0.2
13	0.43631	0.93328	1.9

As can be seen from table 4.7 and 4.8, the probability interval for a collision to happen ranges from [0.02311, 0.42410] to [0.06672, 0.56369]. Over 80% of the encounter cases have lower causation probability interval of the collision, compared with the result without the input of encounter information. For the category which leads to the lowest estimation, the evidence of each variable of encounter situation are as follows: "Time of day= Night", "TCPA=Non-imminent", "Relative bearing=Clear", and "Presence of other vessel=False". Such scenarios indicate that for encounters that happen at night but a clear and non-imminent situation, the likelihood of an accident is the lowest among others. At the same time, the scenario for the highest likelihood of accident would be “Time of day=Day”, “TCPA=imminent”, “Relative bearing=Unclear”, and “Presence of other vessel=True”. Based on the results, one can see that various encounter scenarios could result in different results on causation probability. Such difference can be further utilised to proposed customized mitigation measures for accident prevention.

To integrate all the individual inference result to estimate the causation probability for the region, the weighted average of the probability interval is obtained, which is shown in Table 4.9:

Table 4.9 Combination of the probability intervals

Variables	Yes		No	
	Lower bound	Upper bound	Lower bound	Upper bound
Collision	0.03282	0.47053	0.52947	0.96718

4.6 Discussion

4.6.1 Comparisons among the Models

The credal networks established in this chapter can be considered as a knowledge graph representing the common knowledge on the probability of collision under the joint influence of variables considered. In the previous work, e.g. (Hänninen and Kujala, 2009; Martins and Maturana, 2010; Pedersen, 1995), etc. the causation probability of ship collision is usually modelled in the manner that treats the statistics and information from the macroscopic perspective while the influence of individual encounter is rarely considered. In this chapter, the credal network is built with additional input variables, e.g. “TCPA”, “Relative bearing”, “Presence of other vessels”, etc. The results of the AIS-integrated credal network is performed by making probabilistic inference on each collision candidate obtained and estimate the weighted average of the intervals to combine the individual results. In this section, a comparison between the original model which does not have the input variables, a Modified model that have input variables but without the integration of AIS data, and AIS-integrated model with input variables and probabilistic inference on each collision candidate. The probability interval for variable “Collision” of three models are shown in table 4.10:

Table 4.10 Comparison of three types of causation model

Collision	Yes		No	
	Lower bound	Upper bound	Lower bound	Upper bound
Original model without data variable	0.03663	0.48593	0.51407	0.96337
Modified model with data variable	0.0429	0.5044	0.4956	0.9571
Encounter-integrated model with inputs	0.03282	0.47053	0.52947	0.96718

According to table 4.10, the results of probability intervals for either Collision to happen or not happen fluctuates to some extent. Compared with the original model, the result of the collision to happen in the modified model is [0.0429, 0.5044], which is larger than that in the original model. Such results indicate that the encounter situation and time of day when an encounter happens, have an influence on the collision risk and without considering them, the collision risk between ships could be underestimated. Besides, the range of probabilistic interval is also larger than the original model, which denotes that the uncertainty of the probability of collision also increases. As for the results obtained with a combination of AIS data, both the probability interval and its range decreased. These results indicate that with additional variables considered and input of AIS data to verify each collision candidate, the uncertainty level of the results is reduced, and such results can better reflect the influence of encounter information when modelling causation probability. However, as can be observed from the table, the difference between the results from the three models are not significant, which could be explained by the low topological position of the variables in the model. The influence of variables on the probability of collision will be analysed in section 4.6.2.

4.6.2 Influence of Variables on the Probability of Collision

In the previous section, the effect of considering addition encounter information variables and inputs of AIS data are analysed to verify whether such modification of network can have an influence on the result of probabilistic inference. In this section, the influence of each variable to the collision is analysed in detail.

To perform such analysis, the state of variables are set as evidence one by one, meanwhile maintaining all other variables unchanged. In such a manner, the causation probability interval of the collision, given the corresponding evidence can be then obtained. Besides, the change on a range of intervals of collision probability for each evidence input is also analysed. The results of all states of variables on “collision” are shown in Figure 4.8:

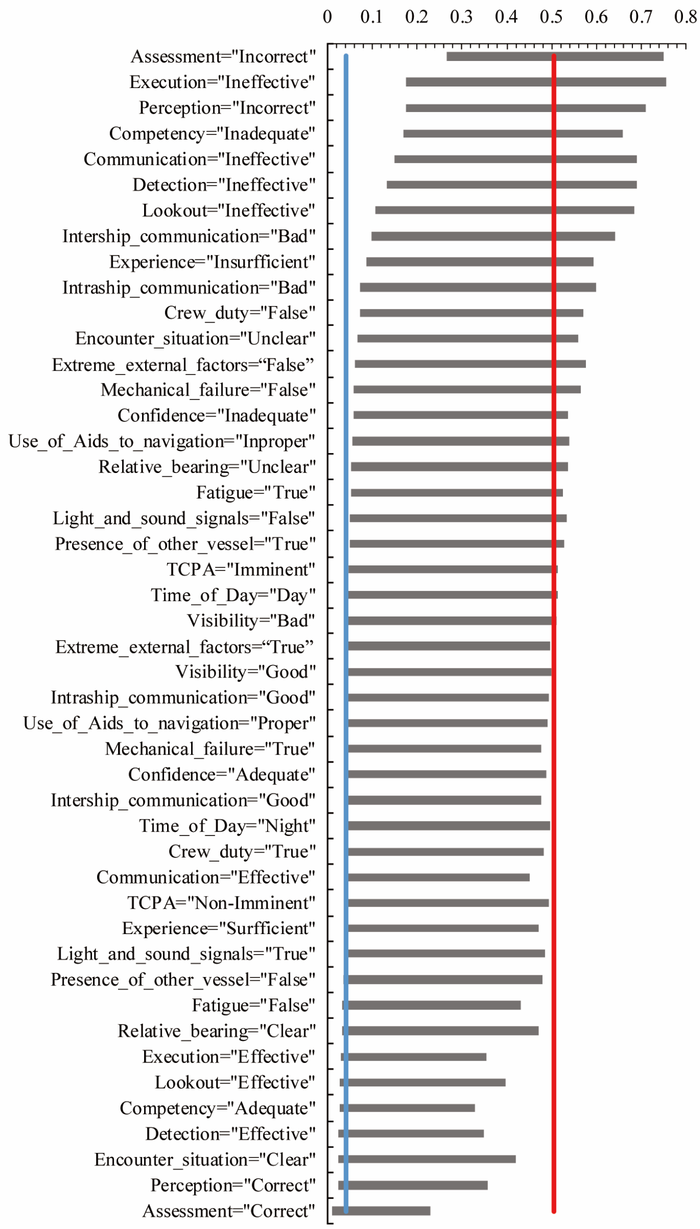


Figure 4.8 Influence of states of variables on causation probability of collision

In figure 4.8, the grey bar indicates the causation probability of collision given evidence indicated by the variables. The blue line represents the lower bound of collision probability, and the red line shows the upper bound of collision probability, respectively. It is evident that "Assessment=Incorrect", and "Detection=Incorrect" result in the largest increment on collision probability. This is because that collision is highly dependent on these variables, and failure in detection and assessment are the main contributors for the collision to happen. Besides, variables such as "Perception=Incorrect", "Competency=Inadequate", etc. also enlarge the probability of collision to different extents. At the same time, "Assessment=Correct", and "Perception=Correct" contribute to the largest decrement of collision probability, which emphasizes the significance of correct perception of the situation and assessment of encounter. As for the input variables, their influence, in general, is not as strong as the influence caused by human and organisational factors in the network. This can explain the small differences between three models to a certain extent that, compared with encounter information, the human and organisational factors can have a stronger global influence on collision probability. However, the clearness of encounter situation also contributes to the third-largest decrement of collision probability, which also highlighted the significance of encounter situation to collision probability.

Since “Assessment=Incorrect” causes the largest change on probability interval, it is also necessary to analyse which state variables could have a strong influence on such state. Figure 4.9 indicates the states of variables that have an influence on the probability of “Assessment=Correct”:

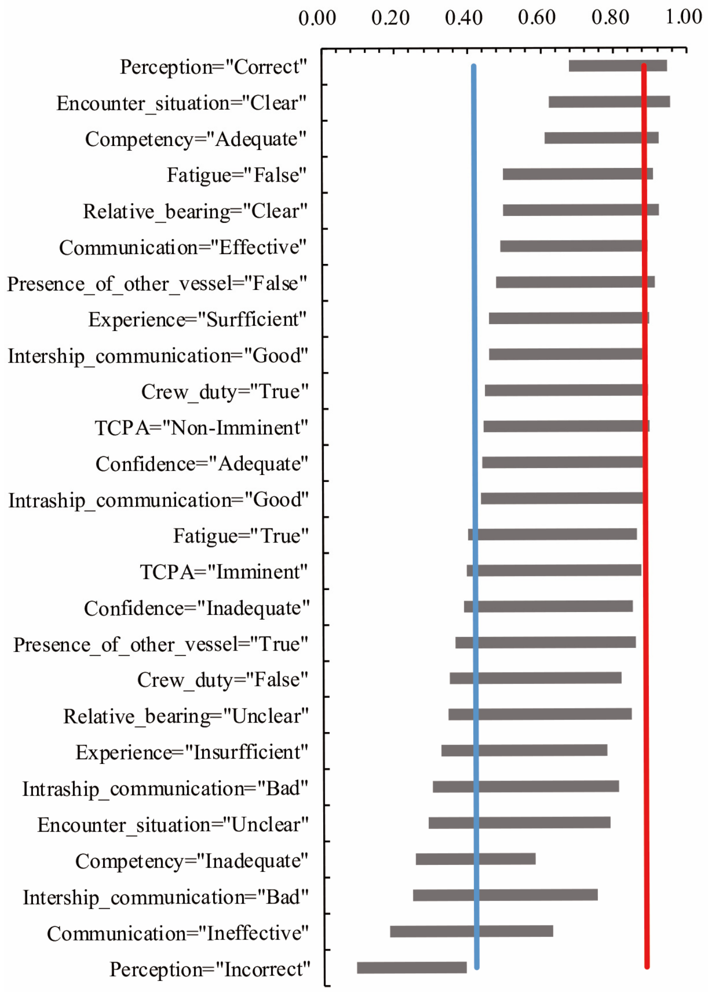
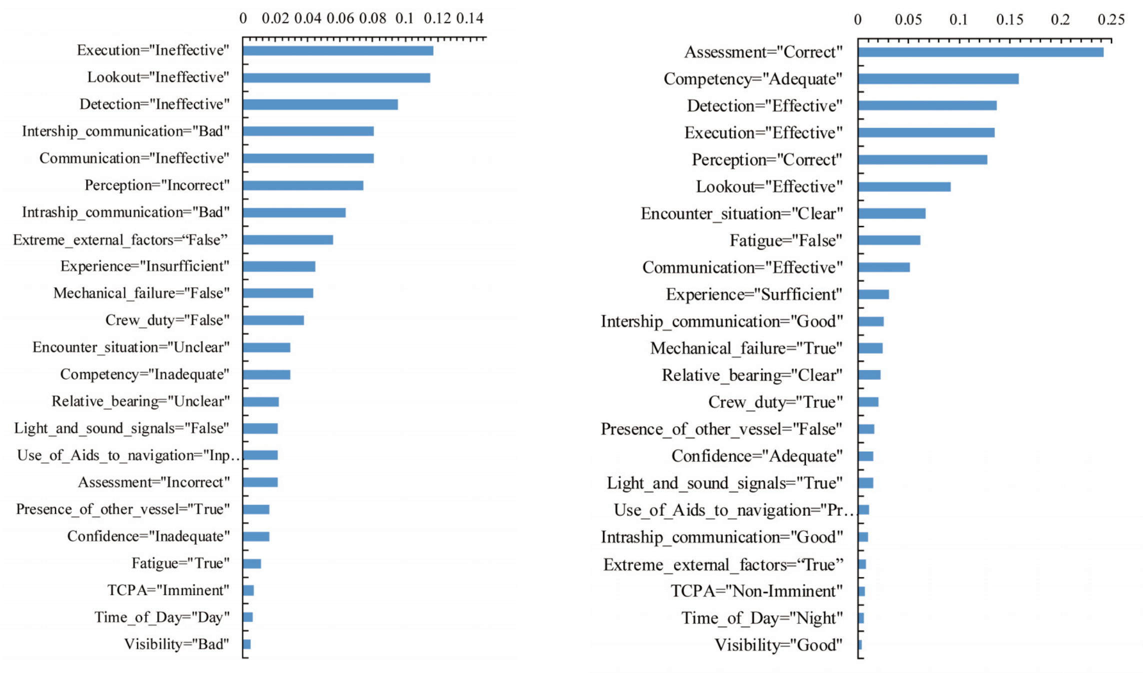


Figure 4.9 Influence of states of variables on the probability of “Assessment=Effective.”

From figure 4.9, one can find that “Perception”, which means whether OOW could recognize the reality correctively, has the strongest influence on probability interval of “Assessment=Effective”, followed by “Encounter situation= Clear”. Besides these states, still, the influence of human and organisational factors are stronger than the rest of the encounter information variables. Based on such finding, we can propose that whether encounter situation is clear of not for determination have a strong influence for effective assessment of the encounter situation, and “TCPA”, “Presence of other vessels”, and “Relative bearing” have a strong influence on the encounter situation. The capability of OOW to recognise reality is another strong influencing factor.



(a) States that narrow down the uncertainty (b) States that enlarge the uncertainty

Figure 4.10 Influence on the Uncertainty of "Collision= True" of each state of variables

Figure 4.10. Illustrates the effects of each state of variables on the range of probability interval, respectively. Such a difference can reflect the change of uncertainty within the result caused by the corresponding evidence. Figure 4.10 (a) indicates the state that can narrow down the interval and variables that have higher topological positions have a stronger influence on the uncertainty. The influence of encounter situation information has a small global influence on the uncertainty compared with variables at high topological positions, which is similar to the influence on the estimate of collision probability.

4.6.3 Potential Applications of the Research

The causation probability analysis of collision accident is an important element for collision risk analysis and management in certain regions for stakeholders such as MSA. The utility of the research can be as follows:

(1) Collision risk analysis

As the important component of collision risk according to the framework proposed by Fujii(Fujii and Tanaka, 1971) and Macduff(Macduff, 1974), causation probability analysis is an indispensable element for quantitative risk analysis on ship collision accident. The result of this research can be integrated with the method of collision candidate detection proposed by the author (Chen et al., 2018) to perform the probabilistic risk analysis for MSA to measure the risk level of the region (e.g. (Goerlandt and Kujala, 2011)) and act as a Key Performance Indicator (KPI)(Valdez Banda et al., 2016b) to evaluate the performance of the MSA (Mou et al., 2019), i.e. the results can perform as lagging KPI to determine if the performance of MAS satisfy the pre-set objective.

(2) Characteristic analysis of collision candidates

For existed risk analysis method, the characteristic of collision candidates can be analysed using their spatiotemporal distribution, i.e. to identify the hot-spot of ship encounters that have potential in space and time domain, e.g. (Zhang et al., 2019a). Based on the results, certain risk mitigation measures, e.g. speed control in certain waterways can be proposed. With the integration of encounter information into the causation models and individual inference for collision candidates, the more detailed analysis can be performed, i.e. based on the individual inference, the collision candidates with a higher risk of collision can be identified, and the spatiotemporal distribution can facilitate the MSA to propose the risk mitigation measures.

(3) Risk management based on sensitivity analysis

With the utilisation of the Credal Network and Bayesian network to establish the causation model. The functionality of sensitivity analysis can be introduced to identify the factors that have a stronger influence on the causation probability of collision compared with all the factors considered. With such findings, the specific management regulation can be proposed to effectively reduce the occurrence of these sensible variables and hence reduce the risk of collision in the waterways.

4.6.4 Limitations of the Research

During the process of causation modelling and probabilities, we have noticed some limitations of the research which need to be improved in the future works to improve the accuracy of the model.

The first limitation is the influence of the region where the accidents occurred and its influence on the accuracy of the model. In our work, we have collected the accident investigation reports where at least one Chinese ship was involved and invited 10 Chinese experts for the knowledge elicitation process. The purpose of this process is to reduce the possible influence of culture on the parameter setting of the model. Due to the limited access of the historical AIS data, to conduct the comparison between the model without the additional encounter information and the model with additional encounter information, we introduced the historical AIS data from Denmark to conduct the analysis on collision candidates. However, in the practice of risk analysis of collision accidents in certain regions or waterways, to improve the accuracy of the analysis, the influence of regional factors in the source of data, and choice of expert should be considered.

The second limitation is the limited consideration of the organisation factors in the model. Many causes identified in the accident investigation report focuses on the unsafe acts and the preconditions that lead to the occurrence of the accident, e.g. failure of communication, failure of the lookout, etc. The organisational factors which could influence the unsafe acts and preconditions are difficult to identify and totally rely on the reports, which have limited the capability of the causation model for more in-depth analysis on the training process, etc. To obtain the whole picture of accident causation factors, an extensive work which needs information from multiple sources, e.g. internal management document from the shipping company, is necessary. When establishing the causation model, there are two types of uncertainties that need to be considered: 1) The uncertainty of the model to be comprehensive; and 2) The uncertainty of the parameter settings of the variables considered. With more accident investigation reports which contain details of a collision accident, the uncertainty of the model to include as many as potential contributing factors can be reduced. In the meantime, the increase on the number of experts invited could also reduce the uncertainty of the parameter setting of the model by formulating the "common knowledge" accepted by the expert group; hence the performance of the model can be improved. To improve the accuracy of the model, in future research, more information which is related to the accident should be included in the analysis.

4.7 Conclusions

The collision between ships is a category of maritime traffic accidents that could result in severe consequences in terms of casualty, economic loss, and environmental pollution, etc. Human and organisational factors are considered as one of the major contributing factors to the occurrence of such an accident. To analyse the risk of such an accident, it is of critical importance to conduct research on modelling the causation risk of collision.

A causation probability model for ship collision accident is proposed with a new approach that integrates the influence of individual encounter situations on the corresponding causation probability from the **micro-to-macroscopic** perspective in this chapter. A Credal Network for causation modelling of collision accident is established based on the historical accident investigation report, HFACS-Coll taxonomy and knowledge from field experts. The encounter information of collision candidate are then extracted from AIS data and are utilised as additional inputs of the network to perform probabilistic inference on each encounter to estimate the causation probability given historical traffic information. The results of the probabilistic inference, comparison, and influence analysis on the data variables are as follows:

(1) Compared with the results from the model without traffic data, as well as the different results for different encounter scenarios, the result of probabilistic inference with the integration of AIS data is modified to reflect the causation collision probability given information on regional traffic and ship encounters. Such findings indicate that causation risk analysis can be conducted in detail to determine which groups of encounters have a higher likelihood of a collision and their distribution in the given region maritime traffic. Such finding can be utilised to identify encounters that satisfy both geometric criteria for collision candidates and the high causation probability of collision and facilitate safety administrations to propose customized safety measures.

(2) Based on the influence analysis of states of variables on the causation probability, the influence of human and organisational factors is larger than variables that reflect encounter situation (e.g. TCPA, presence of other ships, etc.). This could be explained by the low topological position of such variables in the network. In this model, all the geometric data, e.g. "TCPA", "Relative bearing", et al. are located in the lowest topological position in the network, during the inference of probabilities, the influences of these variables are diminished to a certain extent. However, as Fig. 8 and 9 indicate, clear encounter situation have contributed to decrement of collision probability and increment of effective assessment of encounter situation to a large extent. Such finding also emphasizes the significance of clearness of encounter situation to a collision accident.

Within the research, some limitations have influenced the capability and accuracy of the causation model, which are the influence of the region factors in the model and limited recourse on the accident investigation reports and field expert. To improve the capability and accuracy of the method in practices of quantitative risk analysis, the relationship between the accident report, the field expert and historical AIS data should be considered. The increment on the accident report reviewed and experts involved can also improve the performance of the model in future research.

In our work, the causation probability of ship collision accident is estimated with the micro-to-macroscopic perspective for the first time, with the integration of AIS data. It provides a new angle of collision risk analysis to obtain the risk of collision within a specific region and analyse collision candidates in detail at the same time. In the future work, the focus will be on quantifying the epistemic uncertainty, and on refining the model with additional knowledge to improve the results.

Chapter 5 Potential Influence of Maritime Autonomous Surface Ship on Collision Risk

In the previous chapters, a series of new methods for estimating the geometric and causation probability of ship collision accident is proposed. The maritime transportation automation, thanks to the development of modern technology, has been attracting much attention from academia and industry. Therefore, in this chapter, a series of analyses on the potential influence of Maritime Autonomous Surface Ship (MASS) on the probabilistic risk of ship collision in the waterways are conducted to obtain initial insights on the possible situation when MASS was put into application.

The potential encounter types and their proportions in collision candidates are analysed with different Market Penetration Rates (MPRs). The causation probability of ship-ship collision is analysed for different levels of autonomy of MASS and different configurations of the system. The results indicate that the risk of collision in waterways can be expected to reduce with the implementation of MASS. The comparison between different MASS systems provides information on which components would have an influence on the risk of collision that should be focused on. These initial results of the analysis can be beneficial for the development of future MASS.

Acknowledgement: The content of this chapter is the edited version of manuscript submitted to the journal:

Chen, P., Huang, Y., Papadimitriou, E., Mou, J., & van Gelder, P. H. A. J. M. Analysis of the Potential Influence of Maritime Autonomous Surface Ship on Ship Collision Risk in Waterways. Safety Science. (Submitted in Sept. 2019, Under review).

5.1 Introduction

With the rapid development in modern technology, e.g. Artificial Intelligence (AI), Big data technology, Robotics control, etc., the concept of Maritime Autonomous Surface Ship (MASS), has become a hot topic in both academia and industry, with its great potential in improving the efficiency and safety level of the maritime transport system and reducing the economic cost of operation (Ghaderi, 2018; Kretschmann et al., 2017). Such advantages are supported by many proposed or undergoing projects, e.g. ÄlyVESI - Smart City Ferries project (Valez Banda Osiris A and S, 2019), Online risk management and Risk Control for Autonomous Ships (ORCAS) project (Utne et al., 2020), and Maritime Unmanned Navigation through Intelligence in Networks (MUNIN) project (Fraunhofer, 2016; Rodseth and Burmeister, 2015). In these projects, the design of MASS and its feasibility in maritime traffic are verified via quantitative and qualitative risk assessment.

The ultimate goal of MASS is that it can autonomously perform all the navigational tasks during the voyage, including collision avoidance. Various definitions on the level of autonomy are proposed, considering the involvement of human elements and the development of technology for MASS. The IMO has proposed the definition of autonomy level for MASS (IMO, 2018b), which is elaborated in table 5.1. Through the gradual transition from level 1 to level 4 of the autonomy, the influence of human errors (fatigue, detection failure, etc.), which are considered the major contributors to the maritime accident (Chauvin et al., 2013; Martins and Maturana, 2010; Ren et al., 2008) can be reduced.

Table 5.1 Level of autonomy of MASS proposed by IMO

Autonomy level	Definition
L1	Ship with automated processes and decision support: Seafarers are on board to operate and control shipboard systems and functions. Some operations may be automated.
L2	Remotely controlled ship with seafarers on board: The ship is controlled and operated from another location, but seafarers are on board.
L3	Remotely controlled ship without seafarers on board: The ship is controlled and operated from another location. There are no seafarers on board.
L4	Fully autonomous ship: The operating system of the ship is able to make decisions and determine actions by itself.

However, it should be expected that the deployment of MASS will not be a short-term process due to factors from various aspects, e.g. technological and legal issue etc. Furthermore, the conventional manned ship and MASS could co-exist in the maritime transport system before all the individual ships are replaced with MASS. During this process, the Market Penetration Rate (MPR) of autonomous ship, which is used to define the percentage of the corresponding population in the total system (Papadoulis et al., 2019), would be changing. The traffic characteristics in terms of encounters and collision accident would also be dynamically changing. For the stakeholders, e.g. MSA, and port authorities, it would be of critical interest to probe the possible scenarios and obtain initial insights of the potential influence of MASS on the risk of the collision accident.

For the safety analysis of the MASS system, many works can be found in the literature. Some focus on the safety control of MASS during navigation, which includes collision avoidance and path following. Interested readers can be referred to the literature review work by Huang, et al. (Huang et al., 2019a), Campbell et al. (Campbell et al., 2012) and Wang, et al. (Wang et al., 2019) for detailed information. Some works focus on the aspects such as safety level of autonomous ship, development of the safety assessment model for MASS, and the role of the human operator in MASS. Wrobel et al. (Wrobel et al., 2018a, b) conducted series of research on the development of safety assessment model for the remotely controlled ship using System-Theoretic Process Analysis (STPA) from the systematic perspective of MASS. Valdez Banda and Goerlandt (Valdez Banda and Goerlandt, 2018) also applied such a method as one of the step in their work on designing the dynamic Safety Management System (SMS). Ramos et al. (Abilio Ramos et al., 2019) analysed the possible operators' tasks and human failures of the MASS with autonomy level of Remote Control Centre (RCC) using Human Reliability Analysis (HRA) on the different stages of collision avoidance process. Utne et al. (Utne et al., 2020; Utne et al., 2019) analysed the real-time risks of the human operator in the operation of MASS with various level of autonomy using HRA, and proposed framework towards the design of the control system of the autonomous ship with risk analysis functionality. Besides, some works are devoted to analysing the potential impact of automation on human factors in the maritime operation. Pazouki et al. (Pazouki et al., 2018) have investigated the potential impact of ship automation on the situation awareness of human operators and human-automation interaction via experiment simulation under a highly automated environment. Øvergård, et al. (Øvergård et al., 2015) analysed the situation awareness of human operators of dynamic positioning systems during automated ship position keeping. These works have provided a good foundation for the safety analysis of MASS considering the human operator and design for such a system.

In road traffic, many works are focusing on the risk analysis of autonomous vehicles (Katrakazas et al., 2019), and its potential influence in mixed traffic conditions with the transition from manned traffic towards total autonomous traffic (Bhavsar et al., 2017; Morando et al., 2018), etc. One branch of research is to utilise historical accident to predict the potential impact of Autonomous vehicles (Fagnant and Kockelman, 2015; Hayes, 2011). Another approach is to use computer simulation models to analyse the safety level of the mixed traffic with different MPRs (Market Penetration Rates) of autonomous vehicles, e.g. (Morando et al., 2018; Papadoulis et al., 2019). As for the possible influence of MASS on the risk of the maritime accident, especially on collision accident, few works are identified in the literature. Wrobel et al. (Wrobel et al., 2017) have verified the potential impact of unmanned vessels on the maritime transportation safety via analysing the historical accident reports with the question '*what would it be if the ships involved are autonomous*'. Thieme et al. (Thieme et al., 2018) have conducted an extensive evaluation of the applicability of existed risk analysis models to MASS. Several models that have the potential for further development for the risk analysis model of MASS are identified, e.g. Bayesian Network-based approach, simulation-based models, etc. Meanwhile, few works have been done on the risk analysis of mixed ship traffic with the participation of MASS. Therefore, this research could be considered as a pilot study on the potential influence of MASS on the risk of collision in mixed maritime traffic.

To probe the potential influence of MASS on collision risk in waterways, the quantitative risk analysis methods could be utilised to obtain insights into the influence via comparative approach. Due to the early stage of MASS development, it lacks accurate information on the component of the MASS system. However, with the comparative analysis among the level of autonomy of MASS and the MPRs, the trend of risk evolution of MASS and the insights on the potential critical component in MASS to the risk of collision could be obtained. The initial insights obtained in this research can be beneficial for the stakeholders in regional maritime traffic management and future design of MASS.

5.2 Proposed Methodology

As for risk analysis of the maritime accident, various definition, and methods can be found in the literature. Interested readers can be referred to (Goerlandt and Montewka, 2015b) for detailed analysis. The goal of this chapter is to analyse the potential influence of MASS on ship-ship collision risk in waterways. Quantity-based comparative research is conducted following the classic framework proposed by Fujii and Macduff (Fujii and Shiobara, 1971; Macduff, 1974). The MPR and level of autonomy of MASS are considered as major influencing factors in the research. The influence of MASS is analysed in two dimensions: 1) The influence of MASS on ship encounters with different MPRs, and 2) The influence of MASS on the risk of ship-ship collision in waterways. The levels of autonomy considered in this research are conventional manned ship, fully autonomous MASS, MASS with remote control, MASS with remote control via the onboard control unit.

Since currently there is no clear and commonly accepted design of the MASS system in the industry, it is difficult to establish a risk analysis model which can accurately reflect the components of the system and quantitatively measure their risks. Out of this perspective, the objective of our work focuses on the insights obtained from the comparison of results of risk analysis using different MPRs and the level of autonomy of MASS under the framework of collision risk analysis. The research method of this work is shown in figure 5.1:

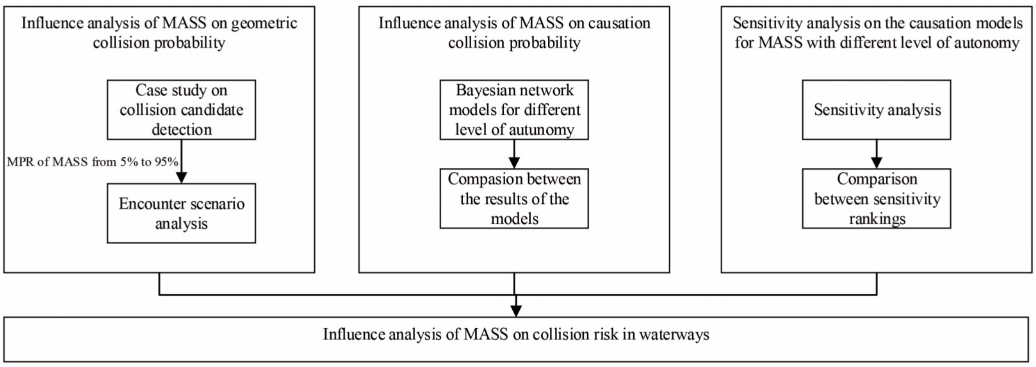


Figure 5.1 Illustration of the scenario-based research method

As for the geometric probability of ship collision, assumptions on different Market Penetration Rates of MASS in the maritime traffic will be applied to analyse the characteristics of the dangerous encounters between ships, and its trend of development with different MPRs. The method proposed in (Chen et al., 2018) will be utilised to obtain the results of collision candidate in a certain region. The goal of this analysis is to probe the potential scenarios of encounters between manned ship and MASS in the waterways under different MPRs and provide information for the collision risk analysis.

For the causation probability, a series of modified Bayesian network models considering the level of autonomy of MASS will be established to obtain and analyse the difference of risk among them. To estimate the potential causation collision probability of MASS, in our research we assume different scenarios of L3 to L4 of MASS and conventional manned ship equipped with aids to navigations facilities, which is also defined as MASS-L1 according to the definition by IMO. The main components and parameters of the networks will follow the materials in the quantitative risk assessment report by DNV GL (DNV, 2003) on the risk analysis of large passenger ship, with certain modifications based on the different levels of autonomy of MASS. The main scenarios assumed in this research are as follows: 1) Conventional manned ship (L1), i.e. the ship is controlled by Officer on Watch (OOW) with facilitation from aids to navigation systems, e.g. radar, Automatic Information System (AIS), etc.; 2) MASS with the onboard control unit, which is the module that is responsible for Guidance, Navigation and Control (GNC) functions of MASS, and also under the control of Remote Control Centre (RCC) operated by human operators, which can directly control the ship when it deems necessary to intervene (L3-I); 3) MASS with RCC via the onboard control unit, i.e. the RCC can intervene in the control of the MASS only via the control unit. It cannot directly control the MASS (L3-II); 4) fully autonomous MASS controlled by the onboard control unit (L4). The difference between these scenarios is the participation of manned RCC and the priority of control between the RCC and the onboard control unit. The goal of this research is to compare the risk level of different levels of autonomy given the same parameter settings on the components of the system and try to probe the critical components of MASS for these levels of autonomy. Combining the results from the two aspects, the potential influence of the participation of MASS in the maritime traffic with different MPR on the collision risk can be analysed.

5.3 Modelling of the influence of MASS on Geometric Collision Probability

The collision between ships (23.2% of the total maritime accident) is one of the major contributors to the maritime accident (EMSA, 2018). To improve the safety level of maritime transport and reduce the occurrence of such accidents, it is of critical significance to perform analysis of collision risk and its characteristics. The results can be utilised by maritime safety administration, port authorities, etc. to propose corresponding risk mitigation measures for maritime safety management.

Out of this objective, various approaches have been proposed and applied to estimate the risk of collision in certain waterways probabilistically. For interested readers, please be referred to the literature review work (Chen et al., 2019c). Due to the scarce nature of the maritime accident, however, it is difficult to conduct such research solely relying on historical records. In the meantime, the collision candidates, also known as near-miss, provides an important perspective for such studies. For ships in encounter situations where their spatiotemporal relationship formulate the collision risk, the accident could occur due to the failure of various factors, e.g. mechanical failure, negligence of target detection, etc.

One of the advantages of implementing MASS is its potential in improvement in navigation safety by eliminating human errors during navigation and collision avoidance.(Abilio Ramos et al., 2019; Wrobel et al., 2018b). During the transition from conventional manned ship to fully autonomous ship, the maritime traffic will be composed of both types of ship. The composition of the collision candidate, i.e. the encounter situation could be as follows: 1) Encounter between manned ships; 2) Encounter between manned ship and MASS, and 3) Encounter between MASSs. For each possible type of encounter, their risk of collision would be different due to the participation of MASS in the encounters. Besides, with different MPRs, the contribution of MASS towards the risk of collision in the traffic compared with conventional ship encounter could also vary. For stakeholders for regional risk management such as MSA, it will be beneficial to have initial insights on the potential situations in the waterways about the collision candidate which concerns MASS and to propose the corresponding precaution measures.

To probe the possible encounter situations with regards to the type of ship involved, an assumption-based analysis utilising the results of collision candidate detection of a certain region is proposed. A case study on collision candidate detection using TD-NLVO method proposed by the author in (Chen et al., 2018) will be conducted to provide the dataset of collision candidates. Based on the result, the ships participating in the two-ships encounters obtained from the AIS data are randomly assumed to be MASS with MPRs varying from 5% to 95%. For each MPR, 100,000 times of random assumption is performed to reduce the uncertainty due to the stochastic nature of the simulation. With the replacement of the ship types, the percentage of each type of encounter among the result is obtained. The trend of their evolutions with the increment of MPR of MASS is then analysed. The flow chart of the method is shown in figure 5.2:

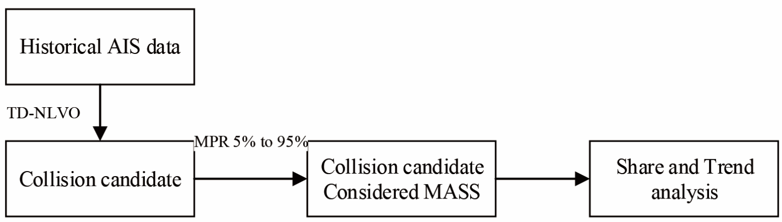


Figure 5.2 Steps for influence analysis on geometric collision probability

5.4 Modelling of the influence of MASS on Causation Collision Probability

5.4.1 Process of Ship Navigation and Collision Avoidance

For manned ships navigating in the waterways, navigation and collision avoidance could be described as the following process (Montewka et al., 2017): 1) Detection: by all means available on board, a watchkeeping is continuously conducted to observe the traffic situation around the own ship and detect the possible risk of collision; 2) Assessment: if there is target ship(s) which is in sight of the own ship, the OOW will evaluate the spatial-temporal relationship between the own ship and target ship(s) to determine if there is risk of collision and the extent of emergency; 3) Action: when the encounter situation and risk of collision is determined by the OOW, a series of collision avoidance manoeuvres, including the change in course or (and) speed, considering the encounter situation and responsibility according to the COLREGs (IMO, 1972), will be proposed by the OOW to avoid the potential collision; and 4) Execution: the steering system (engine, rudder, etc.) will control the movement of the ship to execute the collision avoidance manoeuvre. During this process, various factors, such as failure of the mechanical system, failure of target ship detection, etc. could occur and lead to a collision accident. Causation probability of ship accident is to model the combined influence of such factors on collision accident. In literature, one can find many works following the similar understanding, e.g. Ramos et al. (Abilio Ramos et al., 2019) identified the human error in the operation of MASS following the cognitive model of "Information process-Decision making-Action execution of Crew" (IDAC). Gil et al. (Gil et al., 2019) utilised expert knowledge to analysed the process of collision avoidance of the merchant ship and to identify the priorities of the control actions during the process. In this chapter, we introduce a similar way of thinking to analyse the collision avoidance of manned ship and MASS.

As for MASS, it is reasonable to apply the same process of navigation and collision avoidance during its voyage, as the essence of ship's encounter will still be that ship approaches and then departs from each other safely. The difference between MASS and the conventional manned ship would be the technologies utilised in the processes and the control methods, e.g. controlled by OOW, onboard intelligent control unit, or remote centre according to the levels of autonomy. As shown in (Huang et al., 2020), the research on collision avoidance for MASS and conventional manned ship have many elements in common. Considering this aspect and the necessity for a framework for cooperation between MASS and conventional manned ship in the mixed traffic under COLREGs, we assume that the collision avoidance behaviour of MASS would be similar to manned ship as much as possible.

To model the causation probability, many methods have been proposed based on historical accident reports, expert knowledge, and computer simulation (Chen et al., 2019c). Among them, the Bayesian network-based approach has drawn much attention from academia due to its flexibility in combining various sources of information such as historical data, expert knowledge, etc. This chapter utilises the same approach to conduct the influence analysis and puts the comparison in the same framework.

To establish the causation models for different levels of autonomy for MASS following this logic, a modified Bayesian network model for causation probability of manned ship proposed by DNV GL (DNV, 2003) is introduced as the basis of the causation probability model for the conventional manned ship. A series of Bayesian network models of causation collision probability for MASS with various levels of autonomy, reflected by the change of the structure and Conditional Probability Table (CPT)s of the variables in the model are established to conduct the comparison.

5.4.2 Causation Model for Different Levels of Autonomy

1) Detection

(1) Conventional manned ship (MASS-L1)

According to the historical accident investigation reports and many types of research, failure of adequate target detection due to improper lookout, etc. is one of the major contributors to a collision accident.(Chauvin et al., 2013; Ugurlu et al., 2018). For conventional manned ship, the detection process is performed by the OOW via all the means available onboard, e.g. visual watch keeping, utilisation of aids to navigations (radar and AIS system, etc.). During such process, the failures of the aids to navigations, human errors of the OOWs, e.g. failed to configure the radar to maintain its functionalities, fatigue, etc. could result in the failure of detection of the target ships.

Following the results from DNV's report, the model for failure of the detection process is shown in figure 5.3. The variables can be found in Appendix V.

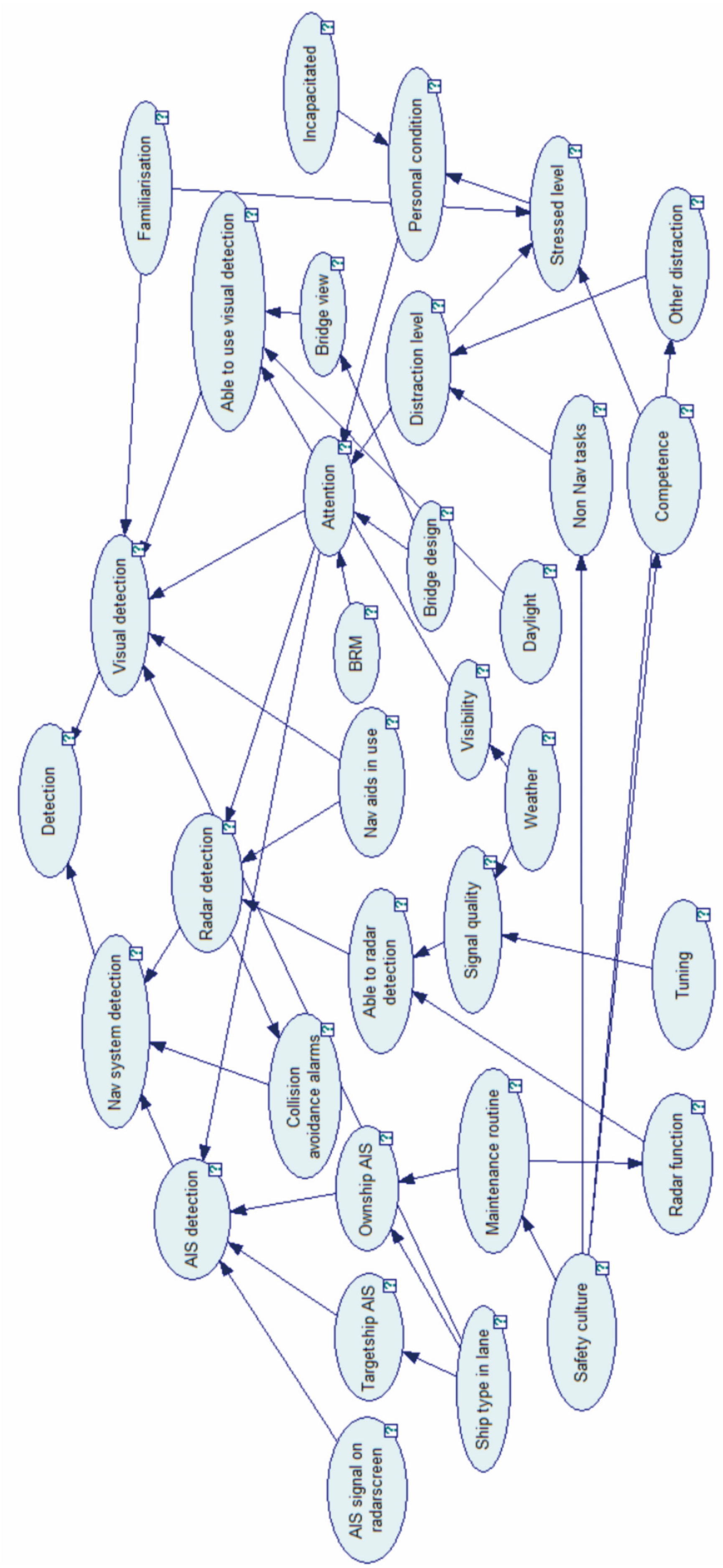


Figure 5.3 Bayesian network model for the detection process of the manned ship (DNV, 2003)

From the model, one can see that the performance of OOWs influences both visual detection function and the navigation system detection function. This can be explained by the fact that during the navigation of the ship, the maintenance of the system and interpretation of the information obtained by aids to navigation is determined by the OOWs.

(2) MASS with Remote Control Centre (RCC) (MASS-L3-I)

With the development of model technology, the autonomous system has the potential to enable the ship to navigate by their own during the voyage. However, for scenarios such as complicated encounters that the control unit could not provide the correct solution in an acceptable time, or human has to intervene to correct the behaviour of MASS; it is necessary to introduce the RCC to improve the safety of MASS via a secured communication link between MASS and RCC. The role of RCC for MASS would be supervising the operation of MASS and intervene when necessary to maintain safety. In this scenario, the MASS can be controlled both by the onboard control unit and the RCC operated by a human remotely. According to the works by (Wrobel et al., 2017) and (Abilio Ramos et al., 2019), the RCC will be operated by experienced seafarers within the working space that can reflect the environment the MASS is in. Such condition could be achieved via a properly designed and equipped facility to present the necessary navigation information to the operators, e.g. monitoring and controlling workstation that monitors critical elements of the MASS (MacKinnon et al., 2015), Virtual Reality (VR) environment, etc. Based on this potential scenario, we assume the influencing factors and structure of failure of RCC to be the same as the OOWs on board, i.e. the model for RCC is assumed to be the same as OOWs in the manned ship. The difference between RCC and OOWs onboard considered in this research are the introduction of a communication link between MASS and RCC and the technologies of detection of targets. Two scenarios for detection facilities onboard MASS are considered: 1) Traditional radar, AIS and remote visual detection, and 2) Traditional radar, AIS, remote visual detection, and possible new detection sensors. The Bayesian network model for RCC is shown in figure 5.4. The causation model for MASS with RCC and variables for potential new sensors and visual detection is shown in figure 5.5 where the model for RCC is integrated into it as a sub-network. The variables can be found in Appendix V.

Figure 5.4 Bayesian network model for RCC (Remote Control Centre)

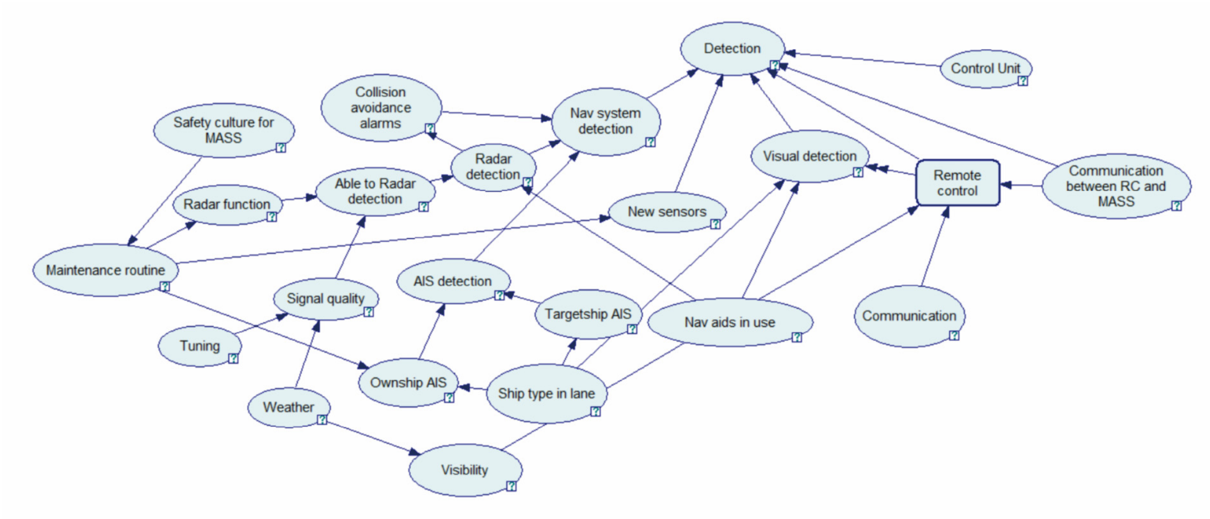


Figure 5.5 Bayesian network model for the detection process of MASS with RCC and potential new sensors and equipment for visual detection

(3) MASS with RCC via onboard control unit (MASS-L3-II)

For MASS with RCC supervising its navigation and operation, another potential alternative design is that remote control is conducted via the control unit on board, i.e. rather than having a control approach that the MASS can be directed controlled by RCC as illustrated in the previous sections, the instructions from RCC must be executed by the control unit of MASS. As for this scenario, we assume the influencing factors and the structure of the detection process of such control method is the same as MASS with RCC, however, the parameter setting for

"Detection" variable is modified to reflect this difference on the relationship between MASS and RCC. The example parameter setting for "Detection" variable is shown in table 5.2, where "Remote control", "Communication between RCC and MASS" is the parent nodes of "Detection" and "Function", "No function", "Yes", "No" are the possible states of the variables.

Table 5.2 CPT of "Detection" for MASS with RCC via a control unit (Partial)

Remote Control	Function							
Communication between RCC and MASS	Function							
Control Unit	Function							
Nav system detection	Yes				No			
New sensors	Function		No function		Function		No function	
Visual Detection	Yes	No	Yes	No	Yes	No	Yes	No
Function	1	1	1	1	1	1	1	0
NoFunction	0	0	0	0	0	0	0	1

(4) Fully autonomous MASS (MASS-L4)

Ultimately, it is expected that the fully autonomous MASS can be introduced into maritime traffic. For this type of MASS, the human errors during the detection process can be eliminated with the replacement of the intelligent control unit onboard the ship and potential new sensors for target detection. However, such system could also fail to fulfil the designed functionality and lead to an accident due to possible contribution from design error of malfunction of the critical components, e.g. the Tesla crash occurred in 2016 (Banks et al., 2018). It is, therefore, necessary to establish a causal model to estimate the potential failure probability. As for the means of detection, it is reasonable to assume that the current aids to navigation, e.g. radar, AIS will still be installed onboard as the fundamental instruments, besides, based on the development of the autonomous system in disciplines such as Autonomous car, Unmanned Aviation Vehicle (UAV), new sensors, e.g. Light Detection And Ranging (Lidar), etc. that can identify the target and send information to the control unit are also likely to be installed. Therefore, as for the detection process for MASS with full autonomy, the Bayesian network models are established via considering the control unit and the possible detection methods. The Bayesian network modes are shown in figure 5.6 and 5.7, respectively. The details of the variables and their parameters settings can be found in Appendix V.

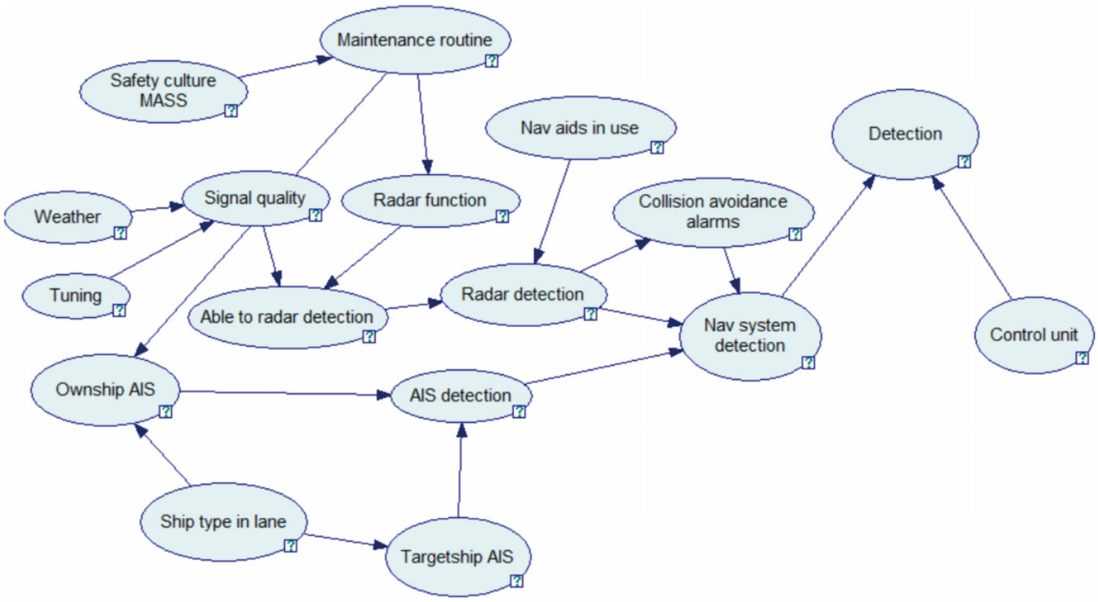


Figure 5.6 Bayesian network model for the detection process of full autonomous MASS without new sensors

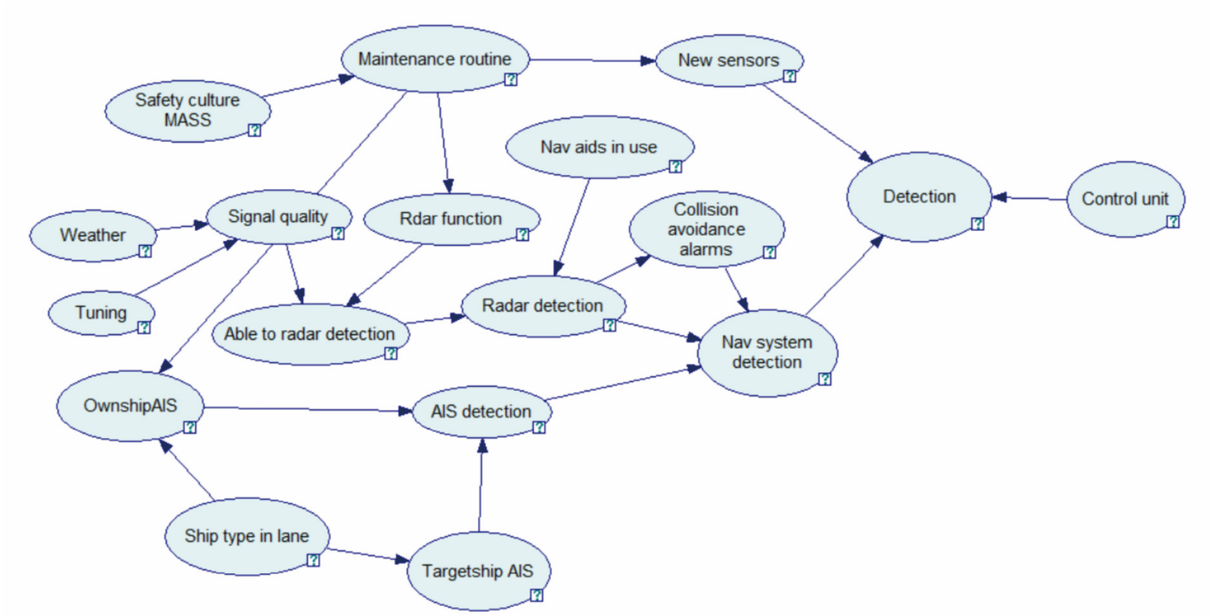


Figure 5.7 Bayesian network model for detection of full autonomous MASS with new sensors

2) Assessment

(1) Conventional manned ship

For conventional manned ship, the assessment of the encounter situation and potential risk of collision between own ship and detected target ships are conducted by the OOW(s) onboard according to the information observed and the regulations such as COLREGs. During such process, the Human-related errors are the most significant contributors to the occurrence of the failure of assessment, ultimate resulting in the occurrence of the accident. Based on the Bayesian network model from the report by DNV (DNV, 2003), the causation model for assessment process of a manned ship is shown in figure 5.8. The details about the variables can be found in Appendix V:

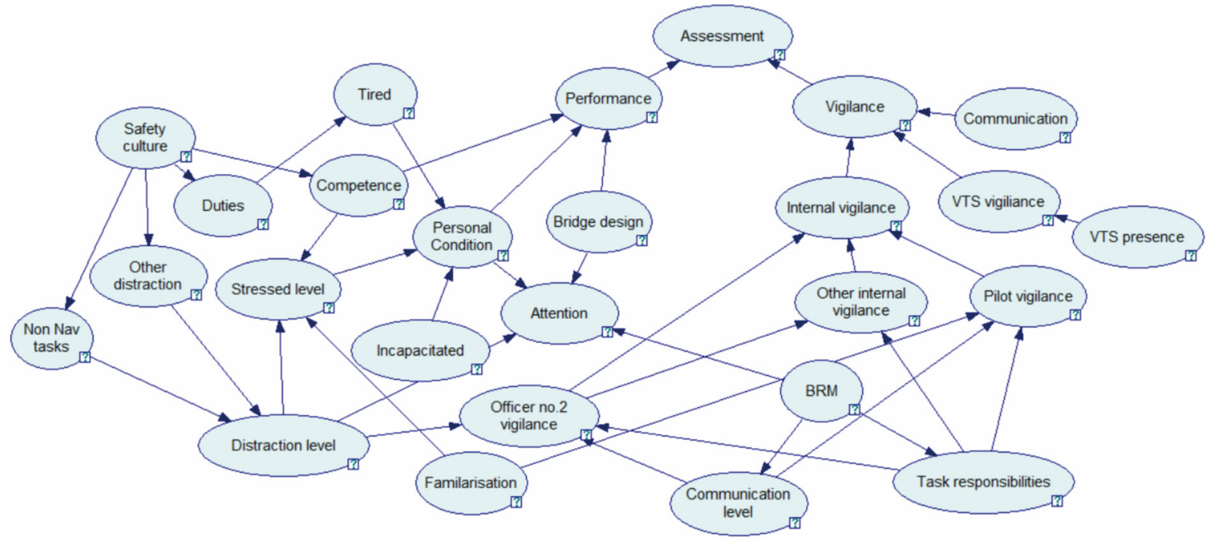


Figure 5.8 Bayesian network model for the Assessment process of the manned ship

(2) MASS with RCC

Compared with a conventional manned ship that the assessment of the encounter situation and risk of collision is performed by the OOW(s), such process will be conducted by the control unit onboard the MASS according to its pre-installed algorithms and RCC when necessary. For the current research on MASS, the collision risk detection methods focus on determining the risk of collision using the following methods: 1) Expert-based method, e.g. Collision risk index, ship domain-based approach; and 2) Model-based approach, e.g. collision criteria based on D/TCPA, dangerous region, etc.(Huang et al., 2019a). For detailed readers, please be referred to (Huang et al., 2019a). The technical details of these algorithms are not considered. In the meantime, a failure rate of 10^{-5} of the control unit is assumed as the parameter of the control unit. This failure rate is at the same level of magnitude of the failure rate of the steering system on board when the maintenance is well conducted. The assessment process of MASS with RCC is shown in figure 5.9. The “Remote control” module in figure 5.9 is a sub-network module which is set with the same variables and configurations as the network figure 5.4 indicates. The details about the variables and their parameter settings can be found in Appendix V:

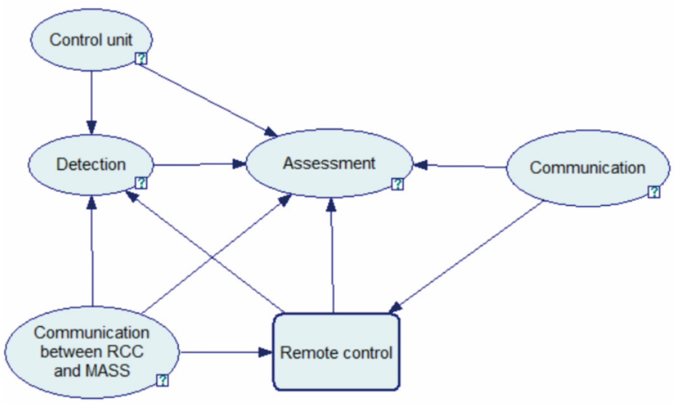


Figure 5.9 Bayesian model for assessment process of MASS with RCC

(3) MASS with RCC via the onboard control unit

Same as the detection process, the difference between MASS with RCC and MASS with RCC via control unit onboard lies in the control priority between the two centres. The Assessment process for MASS with RCC can be conducted by the control unit and RCC individually. As for MASS with RCC via the control unit; however, the control unit plays a more important role in the assessment process, since RCC cannot correct the failure of the control unit. Therefore, the structure of the model for MASS with RCC via a control onboard is assumed to be the same as the aforementioned model. The parameter setting for "Assessment" is shown in table 5.3.

Table 5.3 CPT of the "Assessment" variable for MASS with remote control via a control unit

Remote control	Function							
Communication between RCC and MASS	Function							
Detection	Function				No function			
Communication	Function		No function		Function		No function	
Control unit	Function	No function	Function	No function	Function	No function	Function	No function
Function	1	0	1	0	0	0	0	0
No function	0	1	0	1	1	1	1	1

(4) Fully autonomous MASS

As the highest level of autonomy for MASS, the fully autonomous MASS will process the detection data and determine the encounter situation and risk of a collision via its control unit on board. During the process, the pre-installed algorithm plays the most significant role. The Bayesian network model for the assessment process of fully autonomous MASS is shown in figure 5.10. The details of the variables can be found in Appendix V.

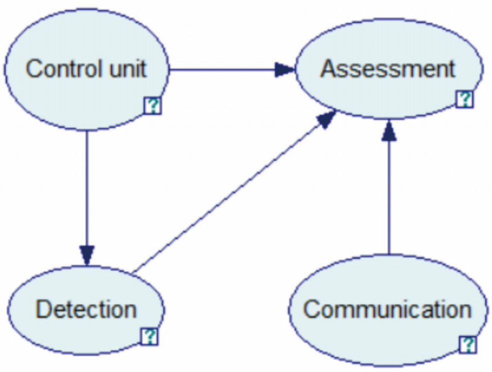


Figure 5.10 Bayesian network model for the Assessment process of fully autonomous MASS

3) Action

(1) Conventional manned ship

After the assessment of the encounter situation between the own ship and target ships and the determination of collision risk, the solution for collision avoidance will be determined by the OOW(s) onboard according to the regulations, e.g. COLREGs and good seamanship. During the process, the errors caused by OOW(s) play a significant role in contributing to the failure of determination of collision avoidance manoeuvre together with the failure in the detection of the target ship. The Bayesian network model for "Action" process of the conventional manned ship is illustrated figure 5.11:

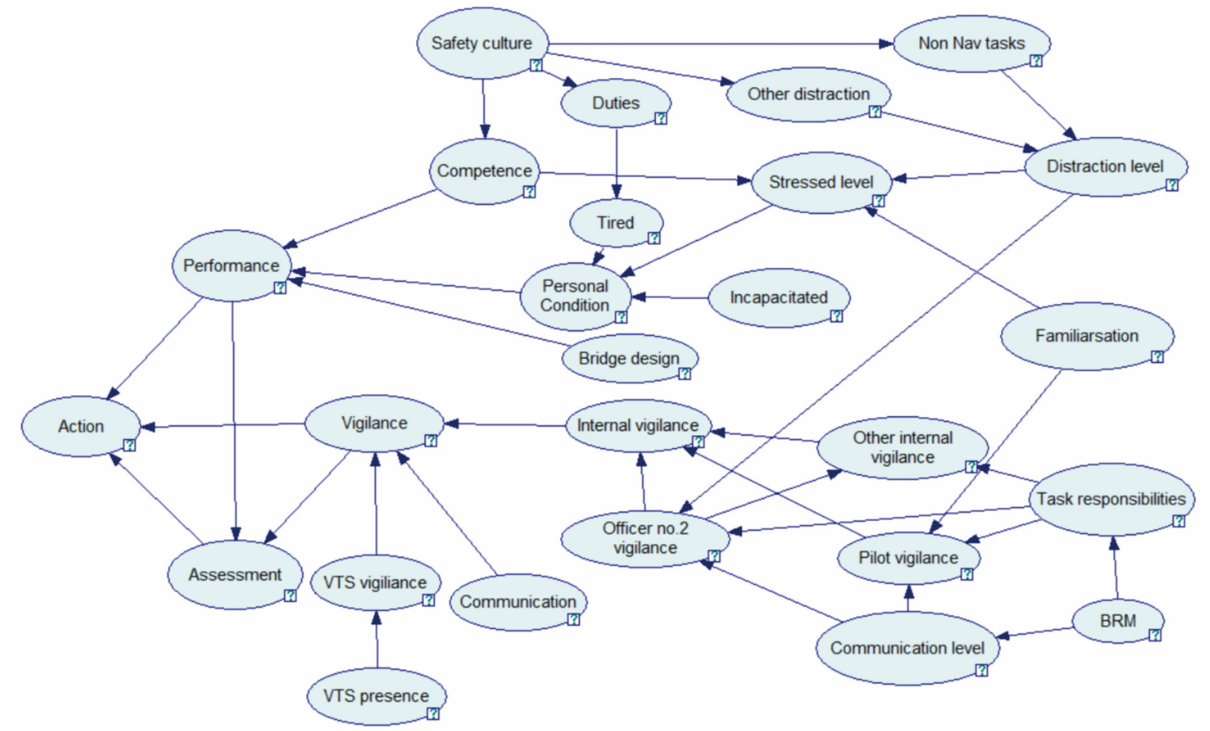


Figure 5.11 Bayesian network model for Action process of the conventional manned ship

(2) MASS with RCC

For MASS with RCC, the assessment process will be conducted by the onboard control unit. If the control unit provided incorrect collision avoidance decision supervised by RCC, or the control unit cannot provide correct collision avoidance solution in the acceptable time limit, the RCC will step in to take over the assessment process. As aforementioned, the model of RCC is established to simulate the model of OOW(s) onboard; therefore, the Bayesian network model for the assessment process of MASS with RCC is shown in figure 5.12:

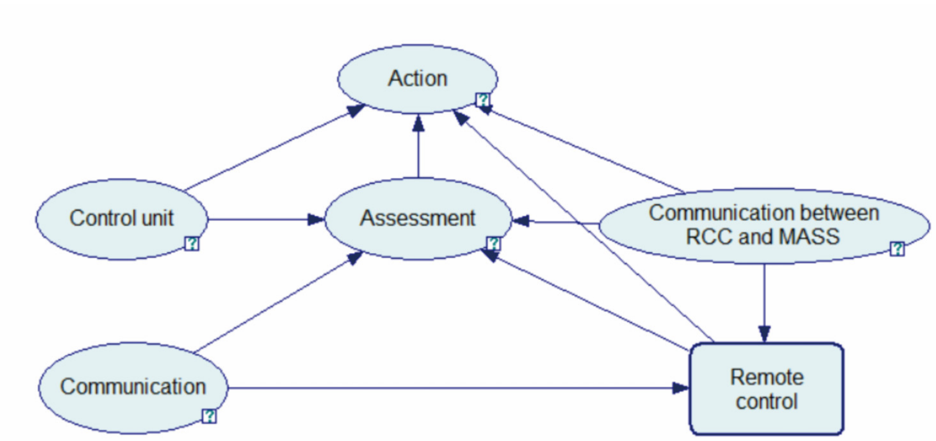


Figure 5.12 Bayesian network model for Action process of MASS with RCC

(3) MASS with remote control via the onboard control unit

Same as the assessment process, the difference between models of MASS with RCC and MASS with RCC via the onboard control unit is also the control priority in the system. For MASS with RCC via the control unit, if the control unit failed, then the action process of MASS will be certain to fail. To reflect this causal relationship, the CPT of "Action" is shown in table 5.4:

Table 5.4 CPT of "Action" for MASS with RCC via the control unit (Partial)

Remote Control	Function							
Communication between RCC and MASS	Function				No function			
Assessment	Function		No function		Function		No function	
Control Unit	Function	No function	Function	No function	Function	No function	Function	No function
Function	1	0.999999	0	0	0.999999	0	0	0
No function	0	1.00E-06	1	1	1.00E-06	1	1	1

(4) Fully autonomous MASS

For fully autonomous MASS, the action process will depend on the control unit according to the information obtained from the assessment process, which is conducted with communication between the own ship and target ships nearby. Therefore, the Bayesian network model for fully autonomous MASS is shown in figure 5.13:

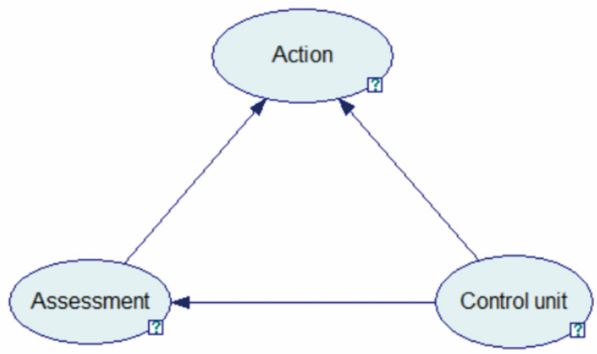


Figure 5.13 Bayesian network model for "Action" process of fully autonomous MASS

4) Execution

For ship navigating in waterways, in regardless of their type, e.g. conventional manned ship or MASS, when the collision avoidance solution is determined and put into action, the rest of the work will be conducted by the steering system on board. For conventional manned ship, the steering system may include rudder, propeller, or azimuth thrusters, etc. The function of these systems is to control the movement of the ship as the controller's decision. For MASS, it is reasonable to assume that the conventional steering system will still be one of the major types of steering systems. However, the new type of steering system, which could maintain the current design of the steering system and also introduce higher reliability, cannot be ruled out of the future design. Based on these assumptions, we propose two Bayesian network models for the execution process for manned ship and MASS, respectively, which are shown in figure 5.14:

(a) "Execution" process for manned ship (b) "Execution" process for MASS

Figure 5.14 Bayesian network model for "Execution" process

5.5 Case Study

To verify the influence of introducing MASS into maritime traffic on the risk of collision accident in waterways, in this section, a series of case studies are conducted to estimate the geometric risk of a collision under different MPRs and causation collision risk for different levels of autonomy. Combining the results from the two parts, the initial insights into the potential influence of MASS on collision risk can be obtained.

5.5.1 The Potential Influence of MASS on Geometric Collision Risk

According to the existing literature and reports, MASS has a very promising potential in improving the safety of maritime traffic and reducing the occurrence of the accident. However, for different MPRs, such influence could be different. Besides, it is reasonable to estimate that the transition from conventional manned ship traffic to fully autonomous MASS maritime traffic could not be short. During the transition period, the conventional manned ship and MASS will coexist in the waterways, and the encounter situation will be significantly different from the current situation.

To obtain an initial insight into what situation could happen with different MPRs of MASS in the maritime traffic, a case study on the encounter type of ships in waterways with MASS in traffic is conducted. A random data set from the historical AIS database from the Danish Maritime Authority is utilised as the sample data to obtain the geometric probability of collision (number of collision candidates). Based on the dataset, 26 encounters between ships are identified, which has exceeded the pre-set threshold for spatiotemporal proximity. An assumption is made here to replace the certain percentage of the ship in the data set as MASS (L4) according to the MPRs. With such an assumption, the encounter type and their percentages in the collision candidate set are calculated with repetition of 10,000 times to reduce the randomness of the assumption. The results are shown in figure 5.15:

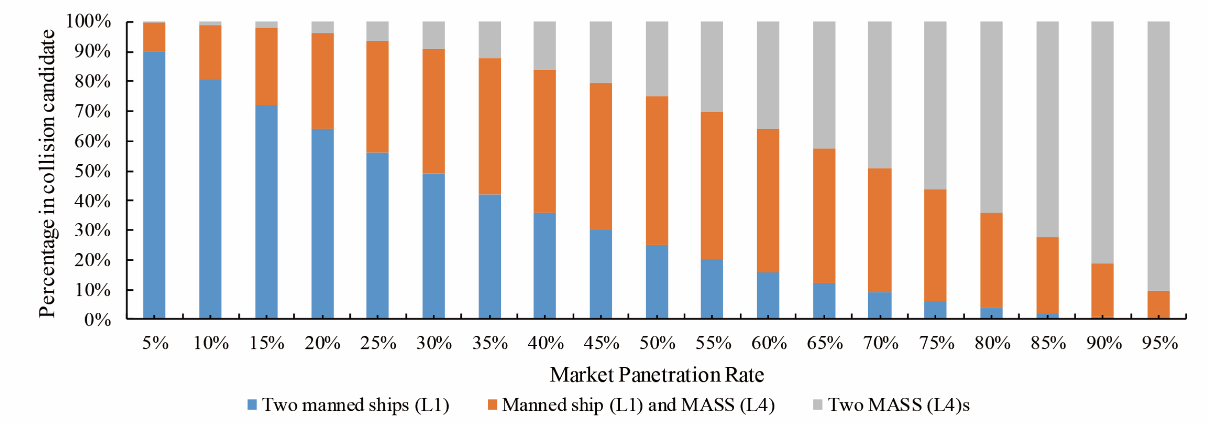


Figure 5.15 Percentages of different types of encounter with corresponding MPRs

As can be seen in figure 5.15, with the increment of the MPRs of MASS in the traffic, the share of the encounter between conventional manned ships is continuously decreasing. Such a trend is reasonable that the MASS in waterways is assumed to be increasing. As for the encounter between conventional manned ship and MASS, the percentage of this type of encounter firstly increases with the increment of the MPRs and then decreases. Another finding is that the increasing rate of the share of the encounter between conventional manned ship and MASS is faster than the MPR’s increment at the initial stage and reach a relatively stable percentage between MPRs of 40% to 60%. This indicates that, at the initial stage of the introduction of MASS into traffic, the encounter between the manned ship and MASS could be more than the encounter between two MASSs in the total traffic.

Based on the results, it is reasonable to suggest that there should be a type of information exchange mechanism between the manned ship and MASS to avoid the potential misinterpretation of the behaviour of MASS. Besides, possible new regulations between them should also be considered, i.e. for encounters between manned ship and unmanned ship, which one will be the stand on ship and the other one to give way in the encounter situation.

5.5.2 The Potential Influence of MASS on Causation Collision Risk

With the development of the 9 Bayesian network models for causation collision risk for a different level of autonomy of MASS and a different configuration of the target detection facilities onboard, the comparison of causation risk between these models can be conducted. It should be noted that the focus of this research is not on the absolute value of the risk estimated by these models; it is the comparative relationships that are focused on. To make the comparison clear, the results from the models are given with a series code to represent, which is shown in Table 5.5:

Table 5.5 Causation probabilities for different causation models and different autonomy levels

Code	Causation model	Autonomy level	Causation probability
CM1	Conventional manned ship	L1	7.835E-04
CM2	Fully autonomous MASS	L4	1.133E-04
CM3	Full autonomous MASS without new sensors	L4	2.167E-03
CM4	MASS with RCC	L3	1.001E-04
CM5	MASS with RCC without visual	L3	1.005E-04
CM6	MASS with RCC without visual and new sensors	L3	2.155E-03
CM7	MASS with RCC via the control unit	L3	1.101E-04
CM8	MASS with RCC via control unit without visual	L3	1.105E-04
CM9	MASS with RCC via the control unit without visual and new sensors	L3	2.165E-03

As can be seen from table 5.5, the causation probabilities of the models for different levels of autonomy with different configurations on the detection instruments vary between the magnitude of 10^{-3} to 10^{-4}. Compared with the conventional manned ship, five types of configuration's causation probability is lower, which indicate that the safety level of the MASS with these configurations will be higher than the conventional manned ship. M4, which is the MASS with RCC, has a collision probability seven times lower than the conventional manned ship. Such results are also consistent with the results from the MUNIN report that MASS around ten times safer than manned ship (Kretschmann et al., 2015). This can be explained with the modifications from the following aspects:1) Enhancement of the detection process with additional detection methods, e.g. visual detection for RCC and potential new sensors to obtain the information in the environment and exclusion of human errors. 2) Additional control methods, i.e. the coexistence of the onboard control unit and RCC via a communication link. Such an approach provides redundancy in the assessment and action processes. As for M3, M6, and M9, however, the causation probabilities are higher than the conventional manned ship, which can be explained by the detection process. Compared with the conventional manned ship, the detection methods for these control models do not have the same level of redundancy provided that the causation probabilities for the common components among them are the same. Compared with the models that have lower causation probability, the detection method for M3, M6 and M9 are limited, i.e. for these three models, the detection process can only be conducted via limited equipment on board, i.e. radar and AIS system. The failure probability of the detection process under such configurations is significantly higher than the rest models, e.g. the failure probability of detection process of M3 is 2.06E-03 while for M1 and M2 such failure probabilities are 5.61E-04 and 1.04E-05, respectively. Considering the assumption that the reliability of radar and AIS system on the autonomous ship are assumed to be higher with the exclusion of human failure onboard, these findings indicate that for MASS, more detection methods should be considered and implemented to ensure the safety of MASS. With such comparisons among different approaches of MASS design, such information could be of help to facilitate the design of MASS to consider the additional detection equipment on board besides the control unit to improve the safety of MASS.

5.5.3 The Potential Influence of MASS on Ship Collision Risk in Waterways

The previous sections illustrate the influence of the introduction of MASS on the geometric collision probability and causation collision probability, respectively, under different MPRs. Via combining the results from these two elements, the potential influence of the introduction of MASS is analysed. The number of collision candidates based on the chosen data set, the percentages of different encounter types under different MPRs and the causation probability of the MASS with RCC and new equipment for detection (M4) is introduced as the causation probability of MASS. Figure 5.16 and 5.17 illustrate the probabilistic collision risk under different MPRs of MASS into maritime traffic and the percentage of contribution from different encounter scenarios, respectively.

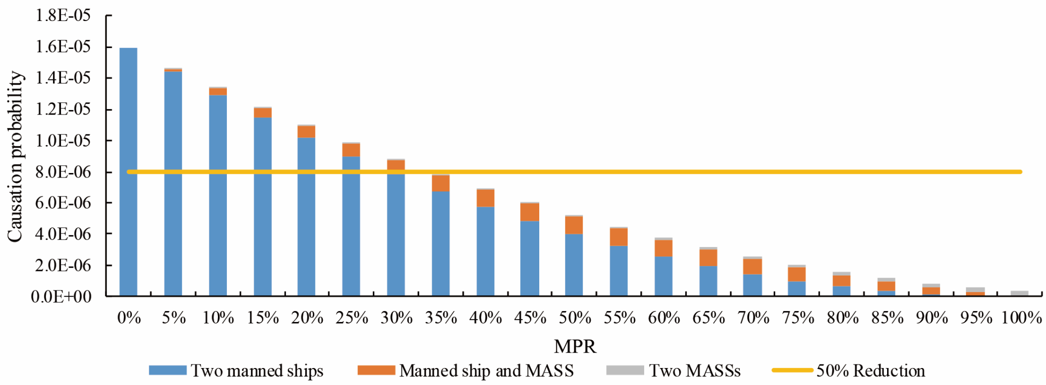


Figure 5.16 Causation collision probability with different MPRs of MASS

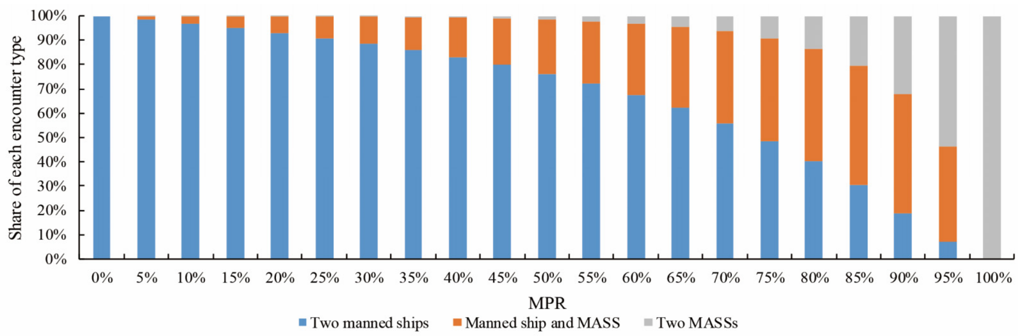


Figure 5.17 Share of encounter type with different MPRs of MASS

According to the figures, it is evident that with the increment of the MPR of MASS, the collision risk in waterways is continuously decreasing. It indicates that the introduction of MASS is beneficial for reducing the collision risk in the waterways. For autonomous vehicles in road traffic, a critical mass, i.e. certain MPR of autonomous vehicles in the road traffic should be introduced to achieve the desired safety effect of automation (Nes and Duivenvoorden, 2017). For MASS, there are few pieces of research which have discussed such topic due to the development of MASS is still at its early stage, and there is no large-scale implementation in the industry. However, from the figure. 5.16 and 5.17 one can see that indeed that certain amount of MASS should be introduced into the traffic to reduce the overall risk of collision, e.g. around 35% of the MPR of fully autonomous MASS should be achieved to reduce the risk by 50% according to figure 5.16. With the decrement of the contribution from the encounter between conventional manned ship, the contribution from the encounter between manned ship and MASS has a trend of increasing, which also denote that such encounter should also be paid attention to improve the safety of navigation.

5.5.4 Sensitivity Analysis

As can be found in many pieces of research and analysis on the collision accident, various influencing factors could contribute to the occurrence of the accident, and human failures are one of the major contributing factors (Chauvin et al., 2013; Ren et al., 2008). With the development of the MASS, many new technologies, e.g. new sensors for detection, advanced onboard control unit, remote control centre, a new type of steering system, etc. will be introduced to facilitate the implementation of MASS. The contribution of these factors to the accident causation probability is of significance to analyse to comparatively discover the changes of their influences under the different design of MASS and obtain initial insight about which factors could be the sensitive factors to improve the safety of MASS. Out of these objectives, in this section, a series of sensitivity analyses are conducted. Inspired by the work by (Hanninen and Kujala, 2012), in this research we introduced the difference between the probability of collision given states on single variable while keeping the rest constant as the indicator for sensitivity analysis. The top 20 sensible variables for the causation models of M1, M2, M4 and M7 are shown in figure 5.18 The results of sensitivity analysis for other causation models can be found in Appendix VI.

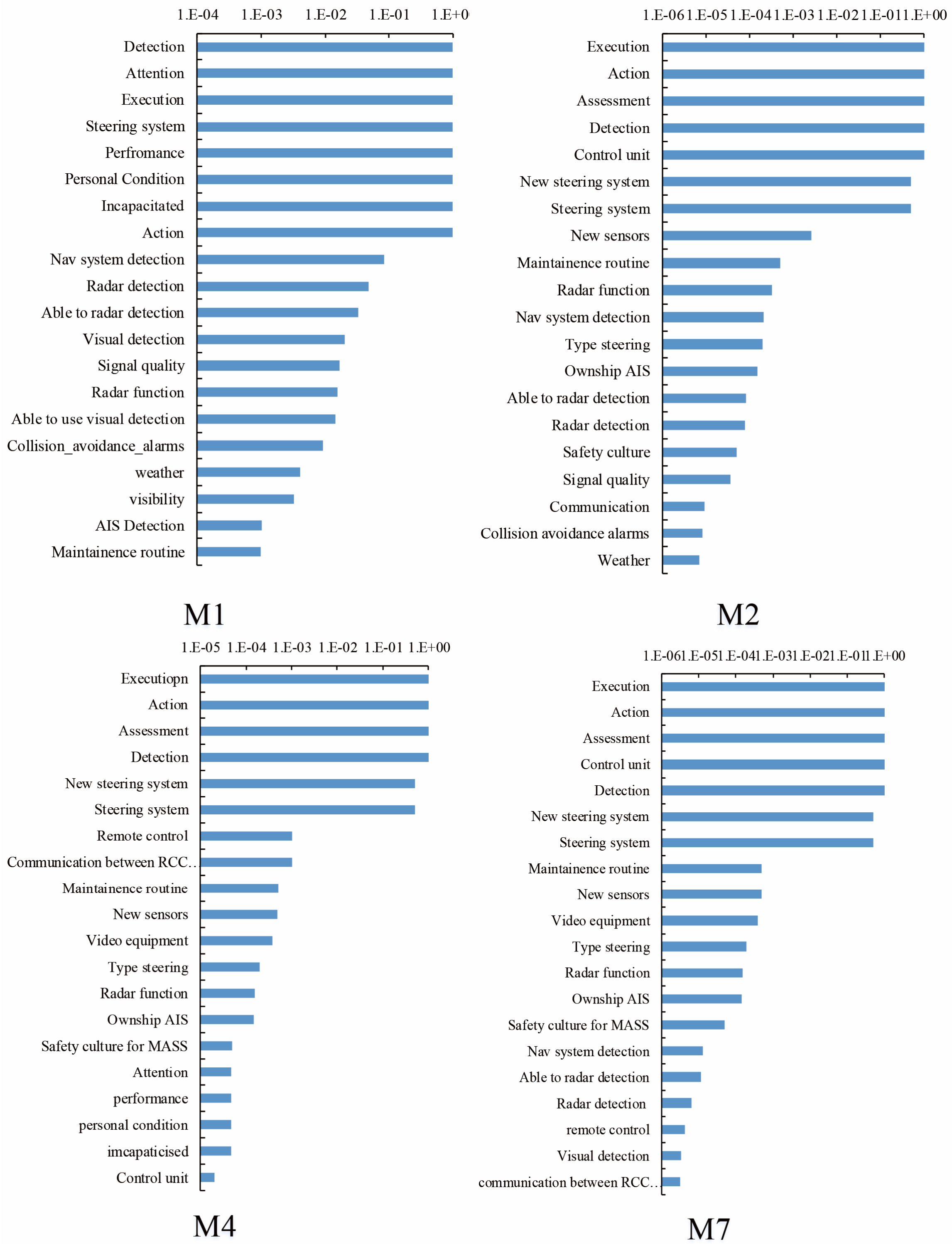


Figure 5.18 Sensitivity analysis for the causation models M1, M2, M4 and M7

As can be seen in figure 5.18 and other sensitivity analyses in appendix VI, for the conventional manned ship, besides the critical process of navigation and collision avoidance, e.g. “Detection” and “Execution” that have a significant influence on the causation probability of collision, the human element “attention” also plays a critical role in the causation model, followed by the “steering system” on board the ship and “performance” of the OOWs. Such results indicate the strong influence of human elements during the collision avoidance process, besides the contributing factors from other components on board ship.

As for the MASS with different control methods, the influence of these variables on the causation probability varies. For fully autonomous MASS with possible new sensors for detection, the control unit (M2), steering systems, and maintenance routine has a stronger influence on the collision risk, which indicates these are the critical component of the MASS system. If the fully autonomous MASS is not equipped with new sensors (M3), the aids to navigation (radar and AIS) would have a higher impact on the result than the onboard control unit. Considering this result and the higher causation probability for this design of MASS, it would be reasonable to suggest that for the detection process of MASS, new sensors that can reflect the navigation environment and detect target ships are necessary for the future development of MASS.

As for M4, which introduces RCC as additional control of MASS, the influence of the steering systems of the ship has become comparatively higher than the rest components of the system. This implies that the reliability of steering system is critical for the safety for MASS as it is for the manned ship, given the possible situation that the "Detection-Assessment-Action-Execution" can be performed by the onboard control unit and RCC independently. However, if the MASS is not equipped with new sensors and equipment for visual detection for RCC, the "Nav system detection" would have a stronger influence on the results than the steering systems, as it is the only solution for target detection of MASS during navigation. For M7-9 which put the onboard control unit at a higher priority than RCC, from the charts one can see that the control unit will have a stronger influence on the causation probability of collision, which is even higher than the M2 which is fully autonomous MASS. Such results indicate that, in order to ensure the safety of MASS with these designs, the reliability of onboard control unit should be paid attention to, provided the reliability of other components of MASS has been realized.

With the comparison, one can find the common components that are critical for the causation risk for MASS: control unit, steering systems, new sensors, maintenance routine, and video equipment for visual detection of RCC. These components have a strong influence on the collision accident of MASS, some of which could directly result in the failure of collision avoidance. With different control methods, such as fully autonomous, combining control unit and RCC, combining control unit and RCC with the control unit in the centre, the priority of these components is different. Such difference could facilitate the researchers to emphasize on the certain component to improve the safety of the system.

5.6 Discussions

5.6.1 Comparisons between Levels of Autonomy

Based on the results in the previous sections, we can see that under the assumptions made in the research, the risk of collision in waterways is generally reduced with the introduction of MASS, in regardless of the control methods. Such a trend is increasing as the increment of the MPR of MASS in the maritime traffic. However, to exploit the advantage of MASS and reduce the collision probability in the waterways, the MPR of MASS in the maritime traffic should be considered, e.g. in our research, with 5% of MPR of MASS the collision probability based on the sample data is 1.46E-05 and such probability reduced to 9.75E-06 with when the MPR researches 25%. Such findings also indicate that a sufficient percentage of MASS should be implemented into the traffic to achieve the desired improvement on safety, e.g. 35% to 40% of

MPR to reduce the risk by 50%. However, due to the limited information on details of MASS, the accuracy of the results could be limited due to the assumptions in work.

As for the different control methods, the influence on the risk of collision is different. The MASS with RCC and equipped with new sensors and can perform visual watchkeeping by the RCC has the lowest level of collision risk among all the configurations of MASS. The MASS with RCC without visual detection functionality, MASS with RCC via control unit and full autonomous MASS also perform better than the conventional manned ship. Considering the assumption that most of the variables in the models are set the same among the causation models, such advantage can be explained by the additional target detection equipment onboard and additional control method such as RCC. If the MASS is designed only with conventional radar and AIS equipment, even with improvement on the reliability of these components via excluding the human errors on detections, the risk of such design is still higher than the conventional manned ship. Based on these comparisons, one can see that the target detection technology for MASS should be improved to achieve this level of safety compared with the manned ship, provided that the reliability of the control unit on board among these control methods are the same.

The communication link between MASS and RCC, in the meantime, also plays a significant role in the system. For such design of MASS with RCC, if the communication link failed, the system will fall into fully autonomous mode, which will increase the risk of collision. The control unit would become the most critical component on board that can lead to the collision accident, based on the sensitivity analysis of the fully autonomous MASS. For these levels of autonomy, in addition to the design of RCC and improving its reliability, how to maintain the reliability of the communication link is also a critical topic to improve the safety of MASS.

During the development towards a maritime traffic system with fully autonomous MASS, the coexistence of MASS and the conventional manned ship will create a type of new encounter situation between manned ship and MASS. Such a situation also needs approaches to let both counterparts to understand their intention during collision avoidance. For conventional ships, such interaction can be achieved by the signal of sound and light, radio communications, etc. according to the navigation regulations, which can be understood by the OOWs on board. To achieve at least some level of interaction, certain approaches of interaction between MASS and manned ship should be proposed for a different level of autonomy of MASS in the future.

5.6.2 Assumptions and Uncertainties

The development of MASS is still at its early stage, and there is no universally accepted framework for the design of MASS, there are many assumptions and uncertainties when analysing its risk due to the very limited information on the system of MASS.

One of the assumptions and uncertainties in the research is the behaviour of collision avoidance of the autonomous ship is assumed to be similar to the manned ship as much as possible, or they share a common framework for such behaviours to understand each other's intentional under the framework of COLREGs. The analysis of the encounter analysis with different MPR of MASS is conducted under this assumption. The reason is based on the fact that current researches on collision avoidance algorithms and models for MASS, which have been comprehensively reviewed in (Huang et al., 2020), have much common knowledge from works on collision avoidance for the conventional manned ship. For conventional manned ship, various indicators such as D/TCPA, ship domains have been utilised to support the risk assessment and collision avoidance during encounters, which have also been widely introduced in the corresponding researches for MASS. Besides, for conventional manned ship, the operation of navigation and collision avoidance is conducted according to the COLREGs. A series of research on rule-compliant collision avoidance operation for the development of MASS can also be found in literature, e.g. (He et al., 2017; Huang et al., 2020). Such works provides good foundation to integrate navigation regulation into the control process of MASS. To avoid potential misunderstanding of intentions between conventional manned ship and MASS, a common framework of behaviour would also be proposed for both types of ships to comply. Therefore, it would be reasonable to assume the design of the onboard control unit would produce similar decisions, or rule-compliant decisions, as to the conventional manned ship under a common framework in the future. However, as the focuses of the research on these two categories are different, the situation where onboard control unit utilises a different method to evaluate the situation and perform the collision avoidance behaviour cannot be ruled out. Under this situation, the encounter situation of the mixed traffic would be different from the current scenarios. Due to the fact that currently there is no wide application of MASS in the maritime traffic, in this research, only the encounters detected in historical AIS data were utilised to analyse the possible situation of the influence by MASS in mixed traffic. As an improvement, a computer simulation-based approach, which can simulate the behaviour of MASS and conventional manned ship and their interactions would be necessary to analyse the possible outcome with a larger sample set quantitatively.

Another assumption and uncertainty lies in the technology and management aspects, e.g. what new technology will be implemented in MASS to achieve its functionality and improve safety, what are their reliabilities on delivering the designed functionality. In the research, due to lacking detailed MASS design, the reliabilities of the new components in MASS are assumed to be higher than that in the conventional ship. The absolute value of the risk analysis in this research under this assumption is not the accurate measurement of the system risk, therefore, cannot be analysed and interpreted individually. However, since the assumed parameters for the variables in the models are set to be the same among the models, the comparative analysis, e.g. the relative risk level among the MASS with different control methods, can provide the initial insights on which approach could provide safer navigation in the future. As for the assumptions in the models, the sensitivity analysis under this configuration can provide information on which variables in the corresponding control methods should be focused on to improve the safety of the system. In the meantime, more detailed information about the technical components on MASS and their reliabilities should be considered in future research to improve the accuracy and reliability of the results. Besides, as many new technologies would be integrated into the development of MASS, the complexity of the system would grow significantly. The influence of increasing the system complexity with introduction of new technologies on the risk of collision of MASS and maritime traffic should also be furtherly investigated in the future.

The third assumption and uncertainty is about the reliability of the control unit of MASS. In the modelling process, the failure rate of the onboard control unit is assumed to be 1E-6, which means in 100,000 times of performance the system will fail one time. Such an assumption has set a considerable high requirement for the reliability of the control unit. For current research on the collision avoidance and navigation control model of MASS, the focus is on the delivery of the designed function effectively and within the time limit. However, the reliability of the control unit or the reliability of it to successfully analyse the situation and conduct collision avoidance under various encounter situations are rarely discussed in the literature. The reliability of the control unit should also be furtherly investigated and analysed when designing the MASS system.

The fourth assumption and uncertainty is about the reliability of the RCC during the operation of MASS. In this research, we assumed that the RCC would function as the bridge group as much as possible utilising all means possible to maintain the situation awareness of the crews in RCC. The contributing factors and their parameter settings are set as the same as those for the conventional manned ship, based on the assumption that the officer in RCC will have the same skill and experience of OOWs on watch and the working environment simulate the conventional bridge as much as possible. However, to achieve such level of reliability of RCC, much effort should be devoted to the training of the personnel and design of the working space. The lack of situation awareness of RCC operator could lead to failure of decision-making during collision avoidance due to the incomplete input from the sensors on board. The work by (Utne et al., 2020; Utne et al., 2019) can be furtherly integrated into the risk analysis of MASS to improve the reliability of RCC.

5.7 Conclusions

MASS is a promising system that could benefit the development of maritime transportation in the near future. In this chapter, a comparative analysis following the framework of quantitative risk analysis of ship collisions to analyse the potential influence of MASS on the collision risk in waterways is carried out.

It is reasonable to expect that the implementation of MASS into maritime traffic will be a smooth transition. Therefore, the research first analyses the encounter situation with a different MPR of MASS from 5% to 95%. The results indicate that before the maritime traffic system is replaced with fully autonomous MASS, there will be three types of encounter situations in the maritime traffic, which are: 1) Manned Ship-manned ship; 2) Manned ship-MASS; and 3) MASS-MASS. The share of the encounters between the manned ship and MASS increases faster than the MPR at the initial stage and reaches its peak value when the MPR reaches 50%. Such finding indicates that this special type of encounter should be paid attention to.

As for research question 4 on the influence on collision risk with the introduction of MASS, the results show that the MASS with RCC as supervisory and secondary control centre has the best performance on safety as it results in the lowest causation risk among the different control methods. The other three control methods, including fully autonomous MASS, also outperforms the safety level of the conventional manned ship. The sensitivity analysis of the causation models has provided information on the common critical components of the MASS system: control unit, steering system, target detection technology, and communication link, etc. With different control methods, the priority of these variables varies. These findings could be utilised to facilitate the design of the MASS in the future.

Due to the fact that there are assumptions in the models to reflect the potential technology utilised in MASS, the absolute value of this research is only a tool for comparative analysis among different MASS systems with regards to their influence on the collision risk in waterways, instead of as the accurate measurement of collision risk in maritime traffic. With the same parameter setting among the models, the comparative research here can provide some initial insights on the risk level of each level of autonomy. With the development of MASS and its design, the model proposed in research can be furtherly improved to obtain more accurate results.

Chapter 6 Conclusions and Future Research

This dissertation proposes a series of novel methods to contribute to the probabilistic risk analysis of ship collision accident in the waterways. The proposed methods change the perspective of analysing the dangerous encounter situations, by considering the encounter as a total process, and introducing the encounter information into the causation probability modelling, in order to explicitly connect the two elements of risk analysis. During the process, multiple sources of information are used, e.g. historical AIS data and expert knowledge. The proposed methods have the potential of obtaining deeper insights into the risk level in the area interested and facilitate the corresponding stakeholders, e.g. MSA, to propose risk mitigation measures to improve maritime safety. Besides, this set of methods has also been applied to analysing the potential influence of MASS on collision risk in waterways to provide insights for the development of autonomous maritime transportation.

The main findings and the answers to the research questions proposed in Chapter 1 are illustrated in Section 6.1. The limitations and recommendations on future research on this topic are then presented in Section 6.2.

6.1 Answers to Research Questions

The objective of this research is to furtherly develop a quantitative risk analysis model for ship collision accident in waterways in an integrated manner that can introduce multiple sources of information into analysis and to further obtain insights of collision risk for safety management. Within this dissertation, the following research questions are addressed:

Main research question:

How can a quantitative risk analysis method be designed for the risk of ship collision, considering multiple sources of traffic information, in order to obtain more insights into the factors contributing to collision risk, and eventually facilitate the safety of navigation in waterways?

To develop the method, the classic probabilistic risk analysis framework proposed by Fujii (Fujii and Tanaka, 1971) and Macduff (Macduff, 1974) is first adopted. A comprehensive literature review on the state-of-the-art of the current development on probabilistic risk analysis of ship collision accident is conducted and presented in chapter 2. The stakeholders, main branches of research methods, and their advantages and disadvantages are discussed in detail. Based on the comparison on the technical approaches introduced for the detection of collision candidates with utilisation of historical AIS data, the Non-Linear Velocity Obstacle (NLVO) approach is introduced in Chapter 3 to establish the Time Discretized NLVO to detect the collision candidates with perspective of encounter process instead of analysing the data with specific time interval. As for the causation probability modelling, the encounter information is added into the modelling process to connect the two-element of risk analysis framework as the contribution, together with the introduction of Credal Network (CN) to perform the probabilistic inference under uncertainty (Chapter 4). As pioneer research, the potential influence of the introduction of Maritime Autonomous Surface Ship (MASS) on the collision risk in the waterways is then analysed following the framework, together with the influence of level of autonomy of MASS in chapter 5.

The detailed answer to the main research question is then presented in the following sub-research question:

Question on the state-of-the-art:
What methods have been proposed for quantitative risk analysis for ship collision risk, and what research gaps are to be explored to improve the research?

To answer this question, a comprehensive literature review focusing on the current development of quantitative risk analysis method for ship collision accident has been conducted following two primary dimensions: 1) Stakeholders of the maritime transport safety and 2) State-of-the-art of the methods.

From the literature, we have identified the following significant participants of the system: 1) Maritime Safety Authority (MSA); 2) Individual Ship. 3) Ship designer and 4) Other stakeholders such as insurance companies, etc. Based on the identification of the stakeholders, one can see that they follow the trend of microscopic stakeholder (e.g. individual ship) to the macroscopic stakeholder (e.g. MSA) that focuses on the risk of collision from the macroscopic perspective, and their interests or concerns also vary, as has been discussed in chapter 2.

Geometric probability modelling, also known as collision candidate detection, is one of the critical elements for probability risk analysis of ship collision. It identifies the encounter between ships that have the potential for collision with the utilisation of various approaches. The literature review has concluded three significant research categories methods:1) Synthetic indicator approach, e.g. utilisation of DCPA, TCPA, etc. and 2) Safety boundary approach, e.g. Ship domain, MDTC, etc. Although the common things among these approaches are that they are all developed to measure the spatiotemporal proximity between ships to estimate the potential for collision, there are some common issues which hinder the development of collision candidate detection:1) Analysing the traffic data at specific time interval with negligence of the encounter process, and 2) Fluctuation of the indicators during the encounter process due to various influences. To solve these issues, a novel velocity-based approach is proposed in chapter 3.

Causation probability modelling describes the influence of the accident contributors, e.g. human and organisational factors, extreme external conditions, etc. on the occurrence of the accident. To model the influence of these factors and quantify the causation probability, the following approaches are introduced based on the literature reviewed: 1) Statistical analysis approach, 2) Fault tree approach, and 3) Bayesian approach. Although many new methods are applied to this topic, the lack of historical data and the respective uncertainty induced has hindered the development of the causation probability modelling. To solve these issues to some extent, a novel Credal Network approach considering the encounter information is proposed in chapter 4.

Question on the geometric probability modelling for ship collision accident:
How can a model be designed to identify and analyse ship encounters, and to obtain geometric probabilities (number of collision candidates)?

To answer this question, a novel velocity-based approach on collision candidate detection method is proposed in chapter 3. Compared with the traditional collision candidate detection methods, the velocity-based approach, especially Time Discretised Non-Linear Velocity Obstacle (TD-NLVO) method, change the perspective of data analysis from instance analysis to encounter process analysis. Such change enables the reduction of duplicate detection due to the multiple times of analysis on the single encounter process. Besides, the introduction of Velocity Obstacle methods as the fundamental methodology in this part unifies the measurement on proximity between ships in space and time dimension, while the traditional methods usually consider these indicators separately, which in some cases could result in contradictory results on collision risk determination.

With the aforementioned improvement, the newly proposed method shows advantages on the robustness on the choice of parameters of the algorithm. The comparison between the traditional methods indicates that compared to the well-known CPA-based method and six other detection methods, the new TD-NLVO method is less sensitive to the values of these parameters. Besides, with the development of the unification of the multiple individual velocity obstacles induced by target ships, the multiple ship encounter situation could also be identified by the modified TD-NLVO, which provides a tool for the development of the method for more detailed encounter analysis of the maritime traffic.

Question on the causation probability modelling for ship collision accident:
How can the causation probability model be designed under limited data and be integrated with the encounter situation information.

To answer this research question, a Credal Network-based method is proposed in chapter 4 to integrate the encounter information into the causation probability modelling and to conduct the probabilistic inference under uncertainty with probability interval.

Firstly, the historical accident report concerning ship collision is reviewed in detail, following the Human Failure Analysis and Classification System (HFACS) method to identify the failures during each stage of ship encounter and collision avoidance operation. Based on which, the causation relationships between them are established. Expert knowledge from 10 field experts includes Captains, etc. are then introduced to determine the parameters of the model.

Secondly, the individual encounter information is integrated into the causation model to connect the two elements of probabilistic risk analysis of ship collision accident and change the causation probability modelling to the micro-to-macroscopic perspective. The results of modelling indicate the encounter information can improve the accuracy of the model and provide detailed causation analysis among the collision candidate, while human and organisational factors contribute to a large extent of the accident occurrence. The proposed method provides a new angle of collision risk analysis to obtain the risk of collision within a specific region and analyse collision candidate in detail at the same time.

Question on the potential influence of Maritime Autonomous Surface Ship (MASS) on the risk of collision in waterways:

What encounter situations could occur in waterways? and What could be the influence on the risk of collision in waterways with different levels of autonomy of MASS, and what could be the critical components of MASS from the safety perspective?

To answer this question, a probabilistic risk analysis of the potential influence of MASS on the risk of collision in waterways is conducted in chapter 5. Following the framework of collision risk analysis, the influence of the introduction of MASS is analysed on the following two aspects: 1) Geometric collision probability, and 2) Causation probability, respectively.

As for the potential influence on geometric collision probability, the concept of Market Penetration Rate (MPR) is introduced to describe the increment on the amount of MASS in the maritime traffic. An assumption is made here to replace part of the ships as MASS according to the MPR to explore the trend of encounters considering MASS, and the results indicate that before the maritime traffic system is replaced with full MASS, there will be three types of encounter situations in the maritime traffic, which are: 1) Manned ship-manned ship; 2) Manned ship-MASS; and 3) MASS-MASS. The share of the encounters between the manned ship and MASS increases faster than the MPR at the initial stage and reaches its peak value when the MPR reaches 50%. As for the potential influence on the causation probability, different levels of autonomy are considered to establish different Bayesian Networks. The results show that the MASS with RCC as supervisory and secondary control centre has the best performance on safety as it results in the lowest causation risk among the different control methods. The other three control methods, including fully autonomous MASS, also outperforms the safety level of the conventional manned ship.

6.2 Recommendations for Future Research

In this dissertation, a series of new methods for probabilistic risk analysis of ship collision accidents is proposed, in order to obtain deeper insights on the accident process and to facilitate the stakeholders to improve the maritime safety in the waterways, both with current, conventional traffic and in future mixed traffic situations (including MASS).

Recommendations on improving the proposed risk analysis methods for practical applications:

This research has still some limitations which should be addressed in future research in order to improve the application of the proposed methods in practices:

1) The regulations on navigation and collision avoidance should be integrated into future research. This can facilitate the development of Velocity Obstacle zones considering the rules of navigation, and determine the role of ships in the encounter process by identifying the potential rule-violating behaviours.

2) A more accurate definition of the safety boundary for collision candidate detection should be integrated into the geometric probability to replace the original assumption of the circular boundary, as to model the difference on the collision risk in the different bearing of ships due to the manoeuvrability characteristics.

3) An improved definition of multi-ship encounter should be integrated into the method as to better describe the start and end of the multi-ship encounter process.

4) More accident investigation reports and information from field experts should be added to improve the accuracy and reliability of the results of accident causation modelling for practical applications.

5) A trajectory prediction model should be developed in case the proposed method is applied on real-time collision risk analysis, as the current method utilises the historical AIS data to construct the trajectories of the ship in the interested area.

Recommendation on the definition of collision candidate detection and the corresponding criteria:

This recommendation is in response to limitation 1 to 3 in the previous section. In chapter 3, a new Non-Linear Velocity Obstacle-based approach for collision candidate detection is proposed and illustrated in detail. The major difference or contribution of the proposed approach is that the perspective of encounter analysis is changed to encounter a process perspective, to avoid potential over/underestimation of the results.

Within the design of the model, the circular shape of the safety boundary is introduced for the simplification of the model establishment. The next step is to furtherly refine such criteria of collision candidate to reflect the common knowledge of safety boundary so as to be consistent with the existing collision risk research. The ship domain, which describes the area around the ship that should be kept clear during navigation (Fujii and Tanaka, 1971), can be a good start point to be integrated into the method.

Secondly, in our research, the influences of navigation regulations such as COLREGs is not included in the process of collision candidate detection. To obtain more insightful information on the responsibility of ships during collision avoidance, COLREGs should be furtherly integrated into the collision candidate detection process.

Besides, due to the differences maritime traffic in different regions, the parameter setting of the proposed method should be calibrated with regional traffic data to better reflect the encounter characteristics in the area of interest to avoid potential over/underestimation.

To facilitate the identification of the dangerous encounter situations from historical AIS data, an improved definition of collision candidate that can accurately consider the process of the multi-in and multi-out of encounter process should be proposed, based on which, the corresponding methods should be revised.

Recommendation on accident causation modelling and accident investigation report processing:

This recommendation is in response to limitation 4 in the previous section. Following the framework of probabilistic risk analysis of ship collision accident, the second element that should be considered is the causation probability of collision, which was induced by multiple accident influencing factors, e.g. environmental factors, human errors, etc.

To improve the model of the causation probability, multiple sources of information should be collected, analysed, and integrated, due to the rare nature of the occurrence of a maritime accident. During the process of data collection, the potential influence of factors such as educational and training level, etc. should also be considered during the process of expert interview and accident investigation, i.e. the choice of the accident investigation report and field expert should be consistent with the characteristics of the research area. Besides, the amount of information in the accident investigation report and expert knowledge should be enough to avoid potential bias in the model to improve the accuracy of the knowledge elicited.

However, as ship collision is a type of maritime accident of low frequency but the severe consequence, the uncertainty of the model and its results should be acknowledged. Methods on uncertainty measurement and reduction should be proposed and integrated to improve the reliability of the method further and provide sufficient information to the decision-makers to understand the uncertainty level of the results.

Recommendation on risk measurement on collision candidate analysis and possible application on real-time collision candidate detection:

For maritime safety management in the waterways, a detailed and real-time analysis of the risk level is beneficial for the stakeholders such as MSA to understand the current risk picture in the area and propose effective risk mitigation measures.

To achieve this objective, a more detailed analysis of the risk components, such as collision candidates, should be considered in future research. The Velocity-obstacle approach provides not only a criterion for identifying the encounters between ships that have the potential for collision, but also a tool to measure such potential with the free space of manoeuvre in the velocity space of the own ship (Huang and van Gelder, 2020). Such an idea can be furtherly integrated into collision candidates detection and analysis as an enhancement for probabilistic risk analysis which gives quantified information on risk levels in the waterways.

Besides, real-time risk analysis and collision candidate detection are also necessary for the stakeholders such as MSA to identify the hot spot in maritime traffic and regulate the traffic to maintain safety. To achieve this objective, in response to the limitation 5 in the previous section, the methods for collision candidate detection proposed in this thesis should be integrated with a trajectory predictor for the ships navigating in the waterways to predict their behaviours based on the observations.

Recommendation on the risk analysis of the application of MASS into maritime traffic:

MASS is a hot research topic that has promising future in improving the safety and efficiency of maritime transportation industry and facilitating the protection of the environment, as it excludes the factors such as human and organisational errors in the process of navigation and collision avoidance and adopts new environmental-friendly technologies. However, it should be acknowledged that there will be a long transition period between conventional traffic model - where all the ships are controlled by experienced ship officers, and the fully autonomous traffic model - where all the ships are autonomously controlled by intelligent algorithms and models. The influence of introducing MASS into maritime traffic should be looked into to provide relevant insights for the stakeholders, e.g. MSA, shipping companies, the general public, etc. to obtain comprehensive understandings of such development and trend.

As for the development of MASS, works such as (Chen et al., 2019a; Li et al., 2019; Xie et al., 2019), etc. provided good examples on how the MASS could be operated and interact with each other autonomously for navigation and collision avoidance. Such detailed information is beneficial for analysing the possible influence of implementing MASS into maritime traffic, with consideration of certain behaviour models of MASS. The results of influence analysis in regards to the special design of MASS and corresponding risk mitigation suggestions could in return provide insights on how the MASS individual could be operated, as we have identified from the literature that research on collision risk analysis avoidance for individual ships and maritime traffic from macroscopic share many common elements(Chen et al., 2019c).

Currently, there are many researchers who have already started exploring these questions, e.g. (Abilio Ramos et al., 2019; Wrobel et al., 2017, 2018b). These works are based on reasonable assumptions on how it would be when MASS is introduced into the traffic. Many insightful arguments are obtained during the research. However, a more detailed analysis should also be proposed based on the development of MASS. Computer simulation of the maritime traffic where MASS is involved could be a promising method. To do this, a series of researches on defining the behaviour of the manned ship, the autonomous ship and their simulation within the maritime traffic system, etc. should be conducted to obtain the details on the potential influence of MASS on safety.

Appendix I Overview of Probabilistic Risk Analysis of Ship-Ship Collision*

Nr.	Research name	Synthetic estimation	
		Geometric probability	Causation probability
1	(Pedersen, 1995)	SB	FTA
2	(Bukhari et al., 2013)	SI	-
3	(Chen et al., 2018)	VB	-
4	(Dong and Frangopol, 2015)	SI	LS
5	(Goerlandt and Kujala, 2011)	SI	LS
6	(Hanninen and Kujala, 2012; Hänninen and Kujala, 2009)	-	BN
7	(IALA, 2009)		LS+EJ
8	(Lusic and Coric, 2015)	SB	-
9	(Goerlandt et al., 2012)	SB	-
10	(Qu et al., 2011)	SI	-
11	(Ren et al., 2008)	-	BN
12	(Rong et al., 2015)	SB	-
13	(Uğurlu et al., 2013)	-	FTA
14	(Wu et al., 2016)	SB	-
15	(Zhang et al., 2018a)	-	BN
16	(Friis-Hansen and Simonsen, 2002)	SB	BN
17	(COWI, 2008)	SB	SA
18	(Kujala et al., 2009)	SB	LS
19	(Debnath and Chin, 2010b)	SI	-
20	(Trucco et al., 2008)	-	FTA+BN
21	(Martins and Maturana, 2010)	-	FTA
22	(Montewka et al., 2010)	SB	LS
23	(Mou et al., 2010)	SI	SA

24	(Debnath et al., 2011)	SI	
25	(Montewka et al., 2012)	SB	LS
26	(Martins and Maturana, 2013)	-	FTA+BN
27	(Silveira et al., 2014; Silveira et al., 2013)	SB	LS
28	(Montewka et al., 2014)	SB	BN
29	(Lenart, 2015)	VB	-
30	(Li et al., 2015)	SI	-
31	(Weng and Xue, 2015)	SB	LS
32	(Zhang et al., 2015b)	SI	-
33	(Debnath and Chin, 2016)	SI	-
34	(Sotiralis et al., 2016)	BN	-
35	(Zhang et al., 2016)	SI	-
36	(Chai et al., 2017)	SI	FTA
37	(Christian and Kang, 2017)	SB	LS
38	(Cucinotta et al., 2017)	SB	LS
39	(Szlapczynski and Szlapczynska, 2016)	SB	-
40	(van Westrenen and Ellerbroek, 2017)	VB	-
41	(Zhang et al., 2017)	SI	-
42	(Zhen et al., 2017)	SI	-
43	(Szlapczynski and Krata, 2018)	VB	-

SI: Synthetic indicator approach; SB: Safety Boundary approach; VB: Velocity based approach;

FTA: Fault Tree Analysis; BN: Bayesian Network; SA: Statistical Analysis; EJ: Expert Judgement; LS: Literature sources.

*This table only illustrates the models which explicitly performs probabilistic risk analysis on ship-ship collision accident for either geometric or causation probability, or both. The works which contribute to the details of methods are not included.

Appendix II Results of Collision Candidate Detection

1. Results of collision candidate detection with standard TD-NLVO

Own ship	Detection period	Target ship	Duration
218XXX000	2018/11/3 7:27:28 to 7:41:55	219XXX261	2018/11/3 7:39:04 to 7:42:05
219XXX416	2018/11/3 8:09:17 to 8:26:37	219XXX477	2018/11/3 8:09:18 to 8:36:10
219XXX416	2018/11/3 8:17:09 to 8:26:07	249XXX000	2018/11/3 8:24:25 to 8:26:16
219XXX416	2018/11/3 8:28:54 to 8:33:47	249XXX000	2018/11/3 8:29:47 to 8:34:10
219XXX416	2018/11/3 8:17:36 to 8:50:20	305XXX000	2018/11/3 8:26:19 to 8:50:29
219XXX477	2018/11/3 8:13:57 to 8:20:45	249XXX000	2018/11/3 8:19:31 to 8:20:56
219XXX477	2018/11/3 8:22:40 to 8:28:21	249XXX000	2018/11/3 8:22:56 to 8:36:30
219XXX477	2018/11/3 8:14:06 to 8:23:45	305XXX000	2018/11/3 8:20:49 to 8:37:59
219XXX903	2018/11/3 8:03:26 to 8:08:07	249XXX000	2018/11/3 8:07:47 to 8:08:15
219XXX903	2018/11/3 8:03:48 to 8:09:26	305XXX000	2018/11/3 8:09:24 to 8:09:35
249XXX000	2018/11/3 8:26:20 to 8:28:30	305XXX000	2018/11/3 8:27:39 to 8:28:49
249XXX000	2018/11/3 8:29:00 to 8:33:32	305XXX000	2018/11/3 8:29:50 to 8:33:54
219XXX261	2018/11/3 14:03:49 to 14:09:00	219XXX477	2018/11/3 14:07:31 to 14:20:26
219XXX477	2018/11/3 14:13:44 to 14:20:43	219XXX081	2018/11/3 14:19:59 to 14:20:55
219XXX477	2018/11/3 14:05:55 to 14:17:28	219XXX903	2018/11/3 14:16:52 to 14:32:18
219XXX477	2018/11/3 14:05:55 to 14:17:17	219XXX000	2018/11/3 14:11:04 to 14:41:23
219XXX477	2018/11/3 14:02:12 to 14:06:32	305XXX000	2018/11/3 14:04:50 to 14:06:37
219XXX081	2018/11/3 14:17:20 to 14:22:07	219XXX903	2018/11/3 14:21:44 to 14:22:12
219XXX081	2018/11/3 14:17:53 to 14:22:36	219XXX000	2018/11/3 14:21:45 to 14:22:50
219XXX903	2018/11/3 14:18:35 to 14:21:10	219XXX000	2018/11/3 14:20:51 to 14:21:26
219XXX903	2018/11/3 14:29:23 to 14:32:51	219XXX000	2018/11/3 14:31:21 to 14:39:20
219XXX081	2018/11/3 18:08:48 to 18:10:22	219XXX903	2018/11/3 18:10:14 to 18:10:26
219XXX081	2018/11/3 21:26:38 to 21:33:11	219XXX903	2018/11/3 21:32:34 to 21:33:31
219XXX477	2018/11/3 23:40:22 to 23:50:23	232XXX136	2018/11/3 23:46:08 to 23:50:55

Appendix III List of Accident Reports Reviewed

No.	Name of the Accident Investigation Report
1	Report on the investigation of the collision between bulk carrier Heraklia and bulk carrier Anping6
2	The investigation report of collision accident between MV maritime friendship and fish boat Guiheyu 80266
3	Report of investigation into the collision between high-speed passenger craft New Ferry LXXXV and Dong Qu Yi Hao
4	Report of investigation into the collision between Hong Kong registered container ship "CSCL Ningbo", and the Chinese registered cargo ship "Jin Hai Da 18."
5	Report on the investigation of the collision between Jin Sheng and Golden rose
6	Investigation report on the collision between MV Hanjin Gothenburg and MV Chang Tong
7	Report of investigation into the collision between "APL Sydney" and "Ming hui yu 0003."
8	Report of investigation into the collision between two Hong Kong registered high-speed passenger ferries Funchal and Santa maria
9	Report of investigation into the collision between The Venetian and Yue Tai Shan 33040 in the estuary of pearl river, China
10	Report of investigation into the collision between "CSCL Hamurg" and "Lian Hua Feng."
11	Investigation report of a collision between cargo vessel Yuzan and Fishing vessel Liao Dan Yu 23935
12	Investigation report on the collision of MV Jing Feng
13	Report or safety investigation on collision between the french tanker Flandre and the RO-RO coaster Hua Chi 8
14	Report of investigation into the collision between China registered bulk carrier Yao Hai and Ukraine registered supply tug Neftegaz-67
15	Investigation report on collision between CMV CCNI Rimac and CMV CSAV petorca
16	Investigation report on the collision between MT "Ginga Tiger" and barge "Zhe Xiao Shan Huo 23651."

17	Report on the investigation of the collision between CMA CGM Florida and Chou Shan
18	Report on the collision between bulk carrier " Ultra Vanscoy" and Fishing vessel "Min Dong Yu" 63285
19	Report of investigation into the collision between Cyprus registered container vessel "RBD Jutlandia" and the Hong Kong licensed fishing vessel "Cm63963A."
20	Report of the investigation into the collision between the Northern Jasper and the Safmarine Meru

Appendix IV Example of Questionnaire

Table 1. Linguistic terms and corresponding probability intervals

Linguistic terms	**Probability intervals**
Virtually certain	(99%, 100%]
Very likely	(90%, 99%]
Likely	(66%, 90%]
Medium likelihood	(33%, 66%]
Unlikely	(10%, 33%]
Very unlikely	(1%, 10%]
Extremly unlikely	[0, 1%]

Table 2. Example of question on the effective lookout. For each scenario, the expert will choose one of the linguistic terms in table 1.

Q12: The probability of effective lookout, under the following scenarios

Competency	**Use of aids to navigation**	**Visibility**	**Communication**	**Lookout**
Adequate	Proper	Good	Effective	
			Ineffective	
		Bad	Effective	
			Ineffective	

	Improper	Good	Effective	
			Ineffective	
		Bad	Effective	
			Ineffective	
Inadequate	Proper	Good	Effective	
			Ineffective	
		Bad	Effective	
			Ineffective	
	Improper	Good	Effective	
			Ineffective	
		Bad	Effective	
			Ineffective	

Appendix V Variables Considered in the Causation Models for MASS*

No	Variable	M1	M2	M3	M4	M5	M6
1	Collision	Boolean logic	Boolean logic	Boolean logic	Boolean logic	Boolean logic	Boolean logic
2	Detection	DNV	Boolean logic	Boolean logic	Boolean logic	Boolean logic	Boolean logic
3	Attention	DNV	---	---	DNV	DNV	DNV
4	Execution	Boolean logic	Boolean logic	Boolean logic	Boolean logic	Boolean logic	Boolean logic
5	Steering system	DNV	DNV	DNV	DNV	DNV	DNV
6	New steering system	---	Assumption	Assumption	Assumption	Assumption	Assumption
7	Control unit	---	Assumption	Assumption	Assumption	Assumption	Assumption
8	Perfromance	DNV	---	---	DNV	DNV	DNV
9	Personal Condition	DNV	---	---	DNV	DNV	DNV
10	Incapacitated	DNV	---	---	DNV	DNV	DNV
11	Action	DNV	Boolean logic	Boolean logic	Boolean logic	Boolean logic	Boolean logic
12	New sensors	---	Assumption	---	Assumption	Assumption	---
13	Video equipment	---	---	---	Assumption	---	---
14	Nav system detection	DNV	DNV	DNV	DNV	DNV	DNV

15	Radar detection	DNV	Modified DNV	Modified DNV	Modified DNV	Modified DNV	Modified DNV
16	Able to radar detection	DNV	DNV	DNV	DNV	DNV	DNV
17	Visual detection	DNV	---	---	Modified DNV	---	---
18	Signal quality	DNV	DNV	DNV	DNV	DNV	DNV
19	Radar function	DNV	DNV	DNV	DNV	DNV	DNV
20	Able to use visual detection	DNV	---	---	---	---	---
21	Collision_avoidance_alarms	DNV	DNV	DNV	DNV	DNV	DNV
22	weather	DNV	DNV	DNV	DNV	DNV	DNV
23	visibility	DNV	DNV	DNV	DNV	DNV	DNV
24	AIS Detection	DNV	Boolean logic	Boolean logic	Boolean logic	Boolean logic	Boolean logic
25	Maintainence routine	DNV	DNV	DNV	DNV	DNV	DNV
26	Assessment	DNV	Boolean logic	Boolean logic	Boolean logic	Boolean logic	Boolean logic
27	ownshipAIS	DNV	DNV	DNV	DNV	DNV	DNV
28	target ship AIS	DNV	DNV	DNV	DNV	DNV	DNV
29	nav aids in use	DNV	DNV	DNV	DNV	DNV	DNV
30	Distraction level	DNV	---	---	DNV	DNV	DNV
31	AIS signal on radar screen	DNV	---	---	---	---	---
32	Bridge Design	DNV	---	---	DNV	DNV	DNV

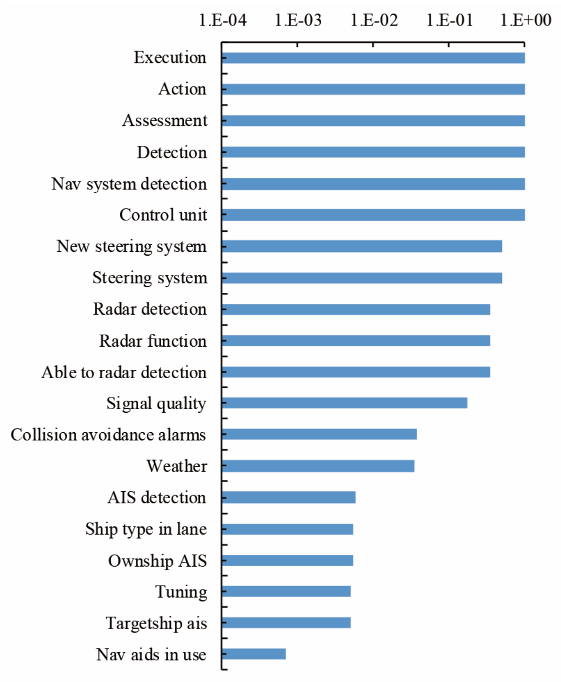
33	pilot vigilance	DNV	---	---	DNV	DNV	DNV
34	Familarisation	DNV	---	---	DNV	DNV	DNV
35	Stressed level	DNV	---	---	DNV	DNV	DNV
36	non nav tasks	DNV	---	---	DNV	DNV	DNV
37	Tuning	DNV	DNV	DNV	DNV	DNV	DNV
38	BRM	DNV	---	---	DNV	DNV	DNV
39	other distraction	DNV	---	---	DNV	DNV	DNV
40	Safety culture	DNV	---	---	DNV	DNV	DNV
41	Safety culture for MASS	---	Assumption	Assumption	Assumption	Assumption	Assumption
42	Communication level	DNV	---	---	DNV	DNV	DNV
43	Ship type in lane	Assumption	Assumption	Assumption	Assumption	Assumption	Assumption
44	bridge view	DNV	---	---	DNV	DNV	DNV
45	Tired	DNV	---	---	DNV	DNV	DNV
46	Vigiliance	DNV	---	---	DNV	DNV	DNV
47	Competence	DNV	---	---	DNV	DNV	DNV
48	Daylight	DNV	DNV	DNV	DNV	DNV	DNV
49	internal vigilance	DNV	---	---	Modified DNV	Modified DNV	Modified DNV
50	task responsibilities	DNV	---	---	DNV	DNV	DNV
51	Duties	DNV	---	---	DNV	DNV	DNV

52	officer no. 2 vigilance	DNV	---	---	DNV	DNV	DNV
53	Communication between RCC and MASS	---	---	---	Assumption	Assumption	Assumption
54	Communication	Assumption	Assumption	Assumption	Assumption	Assumption	Assumption
55	other internal vigilance	DNV	---	---	DNV	DNV	DNV
56	VTS vigiliance	DNV	---	---	DNV	DNV	DNV
57	VTS presence	DNV	---	---	DNV	DNV	DNV

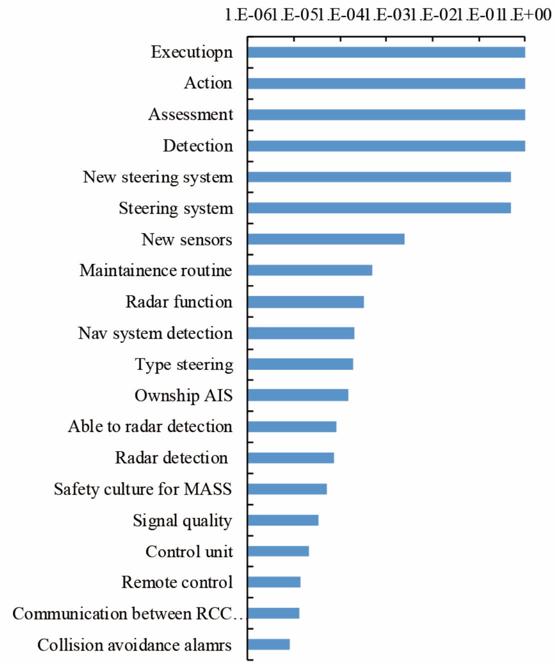
* This table illustrates the data source of the causation models established in our research. The code name M1-M9 denote the causation models, as indicated in section 5.2. For M7-M9, since the structure of the models are the same as M4-M6, respectively, the data source is not illustrated here.

* DNV: Data obtained from quantitative risk analysis report from DNV GL(DNV, 2003); Assumption: Data is set based on certain assumption on the failure rate of the component; Modified DNV: Data are set partially based on DNV's report; Boolean logic: Data are set based on the Boolean logic "AND", "OR".

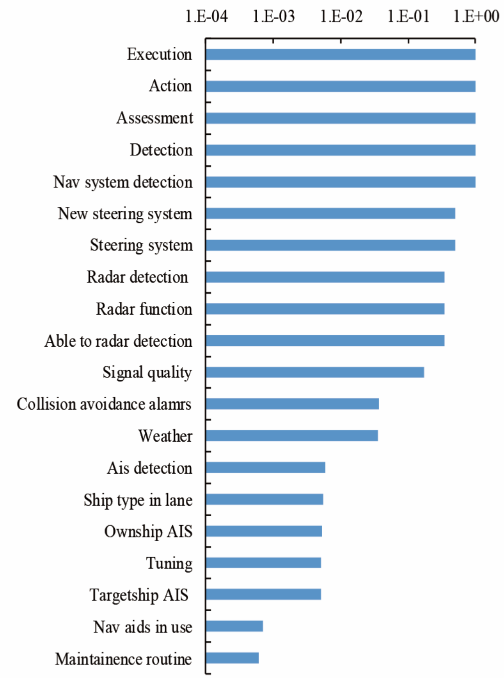
Appendix VI Sensitivity Analysis for Causation Models*



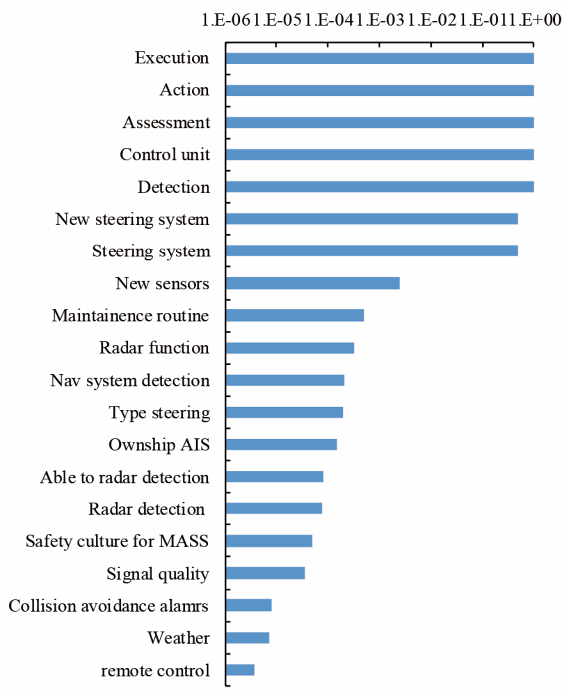
M3



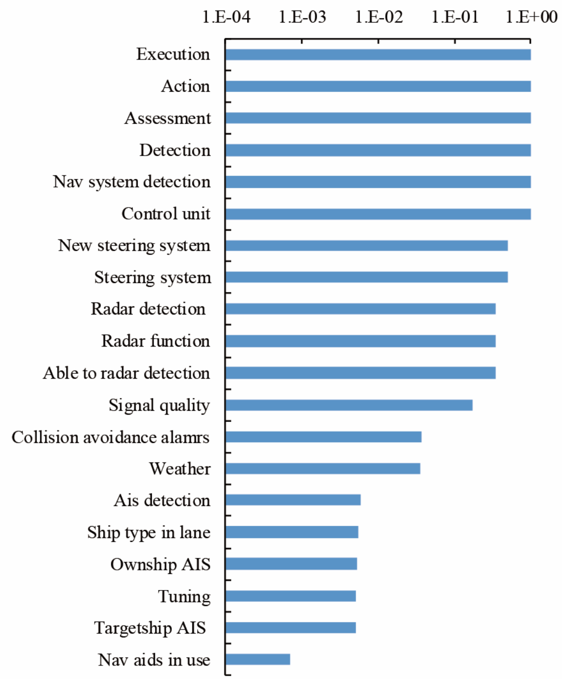
M5



M6



M8



M9

*In this Appendix the results illustrate the sensitivity analysis for causation models of M. The results of sensitivity analysis of conventional manned ship, fully autonomous MASS, MASS with RCC, and MASS with RCC via control unit are shown in section 5.4

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Summary

Maritime transportation is one of the significant contributors to the global economy. Accidents, however, have been posing a risk to individuals and society. Among them, ship collision, due to their severe consequences in terms of loss of human life, property, and environmental pollution, have drawn much attention from the public. Analysing the risk of ship collision and improving the safety of maritime traffic has always been a hot topic for both the academic and industry.

This thesis pays special attention to the probabilistic risk analysis of collision risk between ships in waterways considering multiple sources of information, and the potential influence of the introduction of MASS into the maritime traffic. Specifically, a series of methods for analysing the components of collision risk via multiple sources of information in the area, e.g. AIS data, expert knowledge and accident investigation reports are proposed. The consideration of ship encounter situation is modified to the whole process of encounter to improve the reliability of the results. The information on each encounter is integrated into the estimation of causation collision probability with consideration of uncertainty from limited data availability. With the integration of the two parts, a more comprehensive understanding of the collision risk profile can be obtained which will facilitate the stakeholders such as MSA to propose effective and efficient risk mitigation measures to improve the maritime safety. Besides, with the promising potential for reducing the accident risk by excluding human factors, MASS has been considered as the possible future of maritime traffic. A preliminary analysis of the potential influence of MASS on collision risk has also been conducted to provide insights for its development.

Insights on probabilistic risk analysis for ship-ship collision accident

A comprehensive literature review focusing on the state-of-the-art of probabilistic risk analysis for ship-ship collision is conducted. The stakeholders of the maritime transportation system are identified as follows: MSA, individual ship, ship designers and others. Their interests or

concerns are then identified, which vary from the accident frequency and consequence in the area of interest, conflict detection and resolution to the design, operation and regulation of ship considering risk, etc. considering their position in the macroscopic level of the system. Considering the differences in their preference, we have also proposed recommendations on the choices of the method for collision risk analysis.

A detailed classification and analysis of probabilistic risk analysis methods for ship-ship collision are proposed following the framework of collision risk analysis and the methodological characteristics, e.g. criteria of risk determination, etc. Several major categories of research methods for each risk components are identified: As for geometric probability, synthetic indicator, safe boundary, and velocity-based approaches are considered as the major branches of research while statistical analysis, FTA, and BN are identified as major categories of approaches of causation probability analysis.

From the discussion and comparison between the research methods, several findings are also identified: 1) Research on collision risk analysis from individual and macroscopic perspective have learnt from each other from different levels, and such process could facilitate the development of research methodologies. 2) For geometric probability analysis, spatiotemporal proximity is the most critical criteria for determining the encounter that has potential for collision, which should be the focus of the development of research methods on this component; 3) For causation probability, human and organisation factors contribute more to the failure of the decision-making process of collision avoidance. The lack of data availability is still a problem for comprehensive analysis. The method should be focused on conducting probability inference under uncertainty.

Improved method on ship encounter and geometric collision probability analysis

In this research, a new collision candidate detection method that analyses the whole encounter process between ships instead of instance status of them at a certain time point is proposed.

As aforementioned, the spatiotemporal proximity between ships during the encounter is the critical criteria for risk analysis, the spatiotemporal proximity of the whole process of encounter are projected into the velocity space of ships with consideration of a pre-set safety boundary. Based on which, we proposed TD-NLVO as the new methods for collision candidate detection, the results of which are considered as geometric collision probability. Besides, via integrating the individual VO caused by multiple ships in the encounter situation, an improved version of TD-NLVO is presented to act as the core algorithm for detection of multi-ship encounter scenarios.

A comparison between the proposed method and existing methods that are based on indicators such as CPA, ship domain, etc. are conducted. The results indicate that TD-NLVO has high reliability on the results considering the changes of parameter settings, i.e. the new TD-NLVO method is less sensitive to the values of these parameters compared with the traditional CPA and ship domain-based approaches.

To improve the accuracy and reliability of the results of geometric probability analysis, this research considered collision candidates from the whole encounter process, which is considered as the major contribution. At the same time, the proposed method is also open for criteria which is suitable for regional practices, such as integration of ship domain parameter in the region. Such a method could facilitate MSA to obtain more detailed information on the current risk profile.

Integration of individual encounter information into causation probability modelling

Two issues are identified on causation probability modelling based on the literature review, to contribute to the corresponding solutions, in this thesis, a modified causation probability analysis method that integrates individual encounter information and can perform probability inference under uncertainty due to lack of data availability is proposed.

The method is established following the **micro-to-macroscopic** perspective, i.e. the individual encounter situation can have an influence on the causation probability of collision in the region. To achieve this, several variables that represent individual encounter information, e.g. existence of other ships, relative bearing, etc. are introduced into the model. Besides, CN, which is an extension of BN that can perform inference with uncertainty in the form of probability interval is applied to establish the causation model based on the analysis on accident investigation report following HFACS and expert knowledge as probability inputs. With such a design, the information from AIS data and other sources can be integrated to obtain the results of risk analysis.

The improvements of the proposed method are as follows: 1) The results obtained with this method can provide detailed information on the distribution of causation risk in the encounters obtained with TD-NLVO, which can be utilised to determine the causes for such high risk and facilitate safety administrations to propose customized safety measures; and 2) It indicates that human and organisational factors could contribute more to the occurrence of collision accident, however, a clear encounter situation can also reduce such risk, which emphasizes the significance on the situation awareness of OOW and proper decision and execution during collision avoidance process.

Within the research, some limitations have influenced the capability and accuracy of the causation model, which are the influence of the region factors in the model and limited recourse on the accident investigation reports and field expert. To improve the capability and accuracy of the method in practices of quantitative risk analysis. The relationship between the accident report, the field expert and historical AIS data should be considered. The increment on the accident report reviewed and experts involved can also improve the performance of the model in future research.

The potential influence of MASS on collision risk and maritime safety

MASS is considered to have great potential for improving maritime safety and reducing the occurrence of the accident. To analyse its potential influence on collision risk, following the framework of geometric and causation probability of collision, in this research, a comparative analysis is conducted.

It should be acknowledged that there will be a transition period before the maritime transportation system is totally autonomous; therefore, we have analysed the influence of MASS on ship encounters with MPR from 5% to 95%. The results indicate that at the initial stage on the increment of MPR, the share of between MASS and manned ship increases faster than MPR, and such type should be paid attention to for accident risk reduction.

Multiple models of causation model for MASS considering different level of autonomy (assumption) is established to compare the causation probabilities. The results show that the MASS with RCC as supervisory and secondary control centre has the best performance on safety as it results in the lowest causation risk among the different control methods. Besides, the control unit, steering system, target detection technology, and communication link, etc. are identified as the critical components of the MASS system. Such findings could be beneficial for the development of MASS and facilitate the risk reduction in the future.

In summary, this thesis proposes a series of the method on the components of probabilistic risk analysis of ship collision accident. These methods change the perspective on how we consider the problems, and as the results, some advantages on the results have been brought, e.g. reliability of the results on collision candidate detection, etc. By taking multiple sources of information into the process of collision risk analysis, the results are considered to be more informative so that the stakeholders can be benefited to obtain more clear risk profile and based on which, effective risk reduction measures should be proposed. The proposed methods are expected to facilitate the development of PRA method for ship-ship collision accident and obtain deeper, more comprehensive information for the stakeholders' decision-making process to improve maritime safety.

Curriculum Vitae

Pengfei Chen was born in May 1992 in Luoyang, Henan, China. He obtained the B.Sc. degree on Navigation Technology in School of Navigation, Wuhan University of Technology, Hubei, China, in 2014. At the same year, he started his master programme at the same university under the supervision of Prof. Junmin Mou. He obtained his M.Sc. degree in Traffic Information Engineering and Control from the Wuhan University of Technology in Wuhan, China in 2017.

Starting from Oct. 2016, Pengfei Chen is sponsored by China Scholarship Council as a PhD candidate at the Safety and Security Science Group, the Department of Value, Technology, and Innovation, Delft University of Technology, Delft, the Netherlands, supervised by Prof. dr. ir. P.H.A.J.M. van Gelder and Dr Eleonora Papadimitriou. In his PhD project, Pengfei proposes a series of methods on probabilistic risk analysis of ship-ship collision accident, which consists of methods identifying dangerous encounters that have the potential for collision, and methods quantifying the influence of accident contributing factors on accident risk. His research interests include maritime safety analysis, probabilistic risk analysis, accident analysis, autonomous ships, and maritime traffic management.

Peer-reviewed publications

[1] **Chen, P.**, Huang, Y., Papadimitriou, E., Mou, J., & van Gelder, P. H. A. J. M. (2020). An improved time discretized non-linear velocity obstacle method for multi-ship encounter detection. Ocean Engineering, 196, 106718.

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