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Systems driven intelligent decision support methods for ship collision and grounding prevention: Present status, possible solutions, and challenges

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ABSTRACT

Despite advancements in science and technology, ship collisions and groundings remain the most prevalent types of maritime accidents. Recent developments in accident prevention and mitigation methods have been bolstered by the rise of autonomous shipping, digital technologies, and Artificial Intelligence (AI). This paper provides an exhaustive review of the characteristics of fleets at risk over the past two decades, emphasizing the societal impacts of preventing collisions and groundings. It also delves into the key components of decision support systems from a ship's perspective and undertakes a systematic literature review on the foundations and applications of systems-driven decision support methods for ship collision and grounding prevention. The study covers risk analysis, damage evaluation, and ship motion prediction methods from 2002 to 2023. The conclusions indicate that modern ship science methods are increasingly valuable in ship design and maritime operations. Emerging multi-physics systems and AI-enabled predictive analytics show potential for future integration into intelligent decision support systems. The strategic research challenges include (1) underestimating the impacts of real operational conditions on ship safety, (2) the inherent limitations of static risk analysis and finite numerical methods, and (3) the need for rapid, probabilistic assessments of damage extents. The demands and trends suggest that leveraging big data analytics and rapid prediction methods, underpinned by digitalization and AI technologies, represents the most feasible way forward.

1. Introduction

Maritime transport, the backbone of international trade [1], has flourished under the forces of globalization and urbanization in developing countries. This growth is further fueled by economies of scale and the increasing number of ports, ships, and varied ship types [2]. Despite significant technological advances, improved seamanship standards, and robust assurance frameworks, the severe consequences of ship collisions and groundings still prominently figure in maritime accidents [3]. Although autonomous ships promise to reduce human errors [4–6], their widespread adoption is still a future goal [7–9], leaving critical risks such as oil spills, severe ship flooding, and the loss of human lives (both passengers and crew) as prevalent threats [10–12].

In the dynamic landscape of global maritime operations, the integration of advanced technologies with traditional seamanship practices has become increasingly critical. While the maritime industry has made substantial technological strides, the persistent risk of accidents such as collisions and groundings continues to challenge the safety and efficiency of maritime operations [2]. The development and integration of intelligent decision support systems are pivotal advancements in enhancing navigational safety and operational decision-making [9]. These systems harness emerging technologies like big data analytics, artificial intelligence (AI), and machine learning (ML) to provide predictive insights and proactive risk management strategies. By mitigating

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human errors, which are a predominant cause of maritime accidents, and accommodating the increasing complexity of ship operations in heavily trafficked and environmentally sensitive maritime routes, intelligent decision support systems represent a significant step toward enhancing maritime safety [13,14]. Thus, this paper aims to examine the trends in global maritime accidents and the societal implications of collision and grounding prevention, review the key components of decision support systems for ongoing ships and the fundamentals (theories and their applications) of systems-driven decision support methods, and explore emerging technological trends and requirements in developing intelligent decision support systems for enhancing maritime safety.

1.1. Background

Maritime accidents can have serious negative impacts on marine and coastal ecosystems, on global economic activities, and can even lead to socio-cultural disruptions. To mitigate risks associated with ship collisions and groundings, many techniques have been developed. There are many related literature reviews which collect techniques for maritime risk analysis [15–19], accident damage/crashworthiness evaluation [20–23], and decision support methods for both collision avoidance [7,24] and grounding avoidance [25–27]. The focus of these methods has been on identifying accident frequencies and, as much as practically possible, the associated consequences [28,29]. Historical accident records and traffic data also imply that maritime stakeholders should also improve their perception of risk and understand the value of risk management in ship design and operations. Gil et al. (2020) presents a bibliometric analysis and systematic review of shipboard decision support systems (DSS) for accident prevention, highlighting the rapid growth of new DSS concepts to ensure safety amid increasing ship traffic and reduced manning [30]. In addition, Li et al. (2023) provides a detailed bibliometric analysis of the literature on maritime autonomous surface ships (MASS), focusing on risk and reliability from 2015 to 2022. Their study highlights the evolution of safety and reliability technologies, emphasizing the need for advanced decision-support systems to enhance maritime safety amid increasing ship autonomy and reduced crew requirements [31].

Despite a substantial body of literature on decision support methods, reviews tend to focus on isolated aspects or systems related to ship collision and grounding prevention, often overlooking a holistic systems-driven approach that could benefit the entire maritime domain for the ongoing ships' perspectives. The aims of the present review differ substantially from the existing reviews. This literature focuses on the processes and key components of decision support systems for ongoing ships and points to a significant disconnect between state-of-the-art methods in risk evaluation, damage/consequence estimation, and maneuvering/avoidance determination, and their practical applications on ship operations in real operational conditions. This gap suggests a need for more integrative research that bridges theoretical advancements with real applications in both human-based and intelligent decision support systems. Thus, a review on models, methods, and approaches of systems driven decision support methods a critical need for developing comprehensive frameworks that integrate these various components into a unified, systems-driven decision support system, enhancing the understanding and implementation of ship collision and grounding prevention across ship operations at sea.

The features and processes of human-based decision-making system and intelligent decision support system are presented in Fig. 1. Human-based decision-making systems for collision and grounding prevention are passive, and human errors are still the initial events that lead to the root cause of accidents [32]. This is because decision-making during maritime operations relies on the operator's empirical choices or semi-empirical knowledge (decision support criteria) [33], see Fig. 1. Human errors are categorized into two main types: Known Unknowns and Unknown Unknowns [34,35]. The former refers to errors arising from a recognized lack of knowledge or awareness. Examples include misunderstandings of ship motion uncertainties under varying hydro-meteorological conditions or underestimating potential accident consequences. In contrast, the latter type of human error is more insidious, stemming from a complete lack of awareness about certain risks or factors. This can manifest as misjudging the actions of other vessels or underestimating the severity of a situation. Inevitably, 'Unknowns' of human errors may be converted to 'Knowns' for onboard crews. This can be achieved primarily through the implementation of intelligent decision support systems, utilizing emerging technologies (big data, digitalization, AI, etc.), see Fig. 1. This is because intelligent decision support systems can be utilized to predict forthcoming unwanted events and offer proactive solutions for collision and grounding prevention, thereby

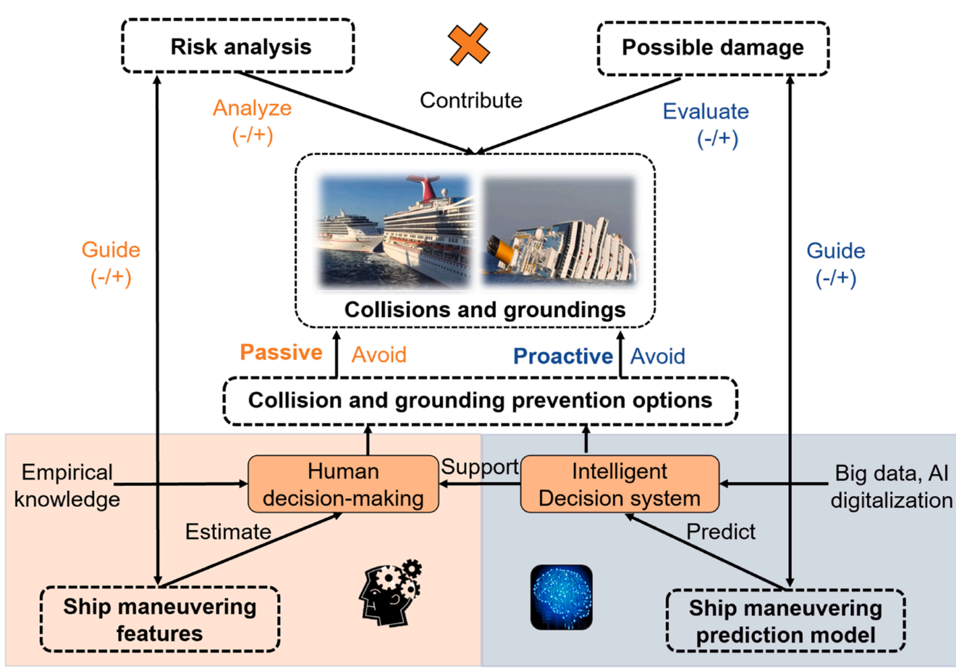


Fig. 1. The processes of collision and grounding prevention in human based decision making / intelligent decision support systems.

enabling the avoidance of such incidents from a proactive perspective [36]. Consequently, such systems have the potential to substantially reduce human errors and prevent maritime accidents.

The key research streams that contribute to intelligent decision support systems and are utilized for maritime risk assessment, mitigation, and accident prevention include:

- **Methods for quantitative risk analysis**. They are primarily used to improve situation awareness and develop frameworks and/or tools for the control of ship operations. Examples of research output are the ship safety domain/zonal methods and decision support criteria (DCPA/TCPA) implemented on bridge systems [7]. In addition, ship motion prediction in real operational conditions provides the possibility for proactive risk management.
- **Methods for damage evaluation/mitigation**. These methods are used to evaluate the crashworthiness and possible damage extents associated with the risk of ship flooding or capsizing that may be followed by loss of life onboard or environmental pollution. The assessment of possible damage is vital in evaluating collisions and groundings, aimed at reducing potential consequences for ongoing ships, especially when such events are unavoidable. Such methods are becoming prevalent for the derivation of risk control options in both ship design and operations.
- **Ship manoeuvring prediction methods for the proactive prevention of collisions and groundings.** To reduce navigation risks and minimize potential consequences, ship manoeuvring should be estimated/predicted for the determination of collision and grounding avoidance potions. Ship motion modelling and prediction methods are increasingly being favoured as the preferred approach for predicting ship motion trajectories and dynamics in real scenarios. To the extent practical, based on iterations, these methods can then be utilized to test and generate safe ship manoeuvring commands for safe operations.

As shown in Fig. 1, the objectives and priorities of human-based and intelligent decision systems differ significantly. In the human-based system, crews try to collect or estimate information about risk situations, ship movements, and potential accident consequences for accident prevention using their empirical knowledge. However, accurately predicting ship motions affected by hydrometeorological conditions, potential accident scenarios and possible damages is challenging for them. This difficulty often leads to human errors and catastrophic accidents. The development of collision and grounding prevention tools for intelligent decision support system in the New Generation of Waterborne Transportation Systems (NG-WTS) is focused on incorporating advanced and rapid prediction and perception technologies, employing theories from ship, safety, and computer science [37]. These technologies are aimed at analysing risks, evaluating potential damages (consequence), and predicting ship dynamics reflecting hydrometeorological conditions. They aim to enhance the reliability of maritime accident prevention decision support option by providing more accurate decision support criteria [38]. In this paper, past technology trends and future NG-WTS requirements are reviewed. This literature focuses on the key components of intelligent decision support systems for ongoing ships. The objective is to review fundamentals and applications of systems-driven decision support methods for ship collision and grounding prevention researched and developed from 2002 to 2023, incorporating perspectives from multiple disciplines. The paper then presents the strategic research challenges, trends, and future directions for the development of intelligent decision support systems. These future systems are intended to enhance the interpretability of human-based decision-making systems in preventing collisions and groundings under real operational conditions.

1.2. Problem description and definitions

The safety assessment frameworks issued by ISO 31000 (ISO, 2018) [39], the IMO (IMO) Formal Safety Assessment (FSA) (IMO, 2002), and the International Safety Management Code (ISM), motivated strategic safety/risk assessment for maritime transportation from the macro-perspective [40]. The fundamental steps of these assessment frameworks are risk analysis (hazard identification), consequence modelling, and risk control options [41]. From the micro-perspective, the International Regulations for Preventing Collisions at Sea-COLREGs (IMO, 1972) are a ship collision prevention regulation [42]. All ships should comply with COLREGs to ensure safe operations during encounters. However, these rules underestimate the complex features of waterways, traffic scenarios, and ship motions in real environments [43,44]. In addition, they do not account for effective decision support. This is the reason why human errors play an important role, i.e., the crews are inevitably involved in ad-hoc decision-making during operations [45]. The study pointed out that 56 % of major collision accidents are caused by violations associated with ignoring risks under extreme conditions [46].

Traditional collision and grounding assessment methods focused on quantitatively analysing spatial-temporal relationships between ships or ship-to-rock encounters (see Section 4). However, the effects of possible damages and the influence of the surrounding environment (e.g., weather conditions or ship motions) are not evident part of this process [47,48]. Thus, collision and grounding risk assessment ignores the influence of real conditions during operations [43], ship maneuvering characteristics [49] and possible consequences [50,51], which may result in onerous warning errors and missing critical scenario detection/realization.

As shown in Fig. 2, the critical domain surrounding ship operations may be divided into 3 areas based on ship maneuvering characteristics, namely (a) area 1 defined as a casually dangerous zone pertaining to close proximity to a ship or a rock; (b) area 2 where safety is prevalent and (c) area 3 where high risk is evident. From a pragmatic ship operations perspective, accounting for ship evasiveness and accident consequences areas 1 and 2 may be considered safe. However, in area 3, there are three possible results, namely (a) near-miss scenarios, (b) collision and grounding accidents leading to minor damages, and (c) major damage scenarios leading to major loss. Lack of situation awareness on the operations in these areas is one main limitation of existing methods/frameworks.

For a ship, collision and grounding assessment should be considered systematically, by analyzing the probability of occurrence as well as potential damages. Additionally, ship manoeuvring commands for collision and grounding avoidance should be optimized to reduce navigation risks, taking into account the ship's ability to respond to motions. Therefore, for an intelligent decision support system, the valuation function can be represented as follows:

$$F\ (t) = P_C\ (t) * C_C\ (t) + P_g\ (t) * C_g\ (t) \tag{1}$$

where $F\ (t)$ denotes the valuation function of collision and grounding risk assessment in time (t), functions $P_c\ (t)$ and $P_g\ (t)$ present the probability of collision and grounding, and functions $C_c\ (t)$ and $C_g\ (t)$ present the correspondent damages. Probability and consequence assessment may incorporate static information (e.g., ship geometry and scantlings, rock geometry, hull material, and profile) as well as ship motion information (e.g., collision/grounding locations, angle of impact from the striking ship, angular and translational velocities) [36].

As described in Eq. (1), the function aims to find a solution to prevent an accident at the lowest value of $F\ (t)$, where the probability of occurrence is 0. Otherwise, the focus is on minimizing the penetration and damage lengths [52]. This is achieved by predicting ship motions and quantifying the valuation function $F\ (t)$, when its termination criterion of navigation is satisfied (safest collision and grounding

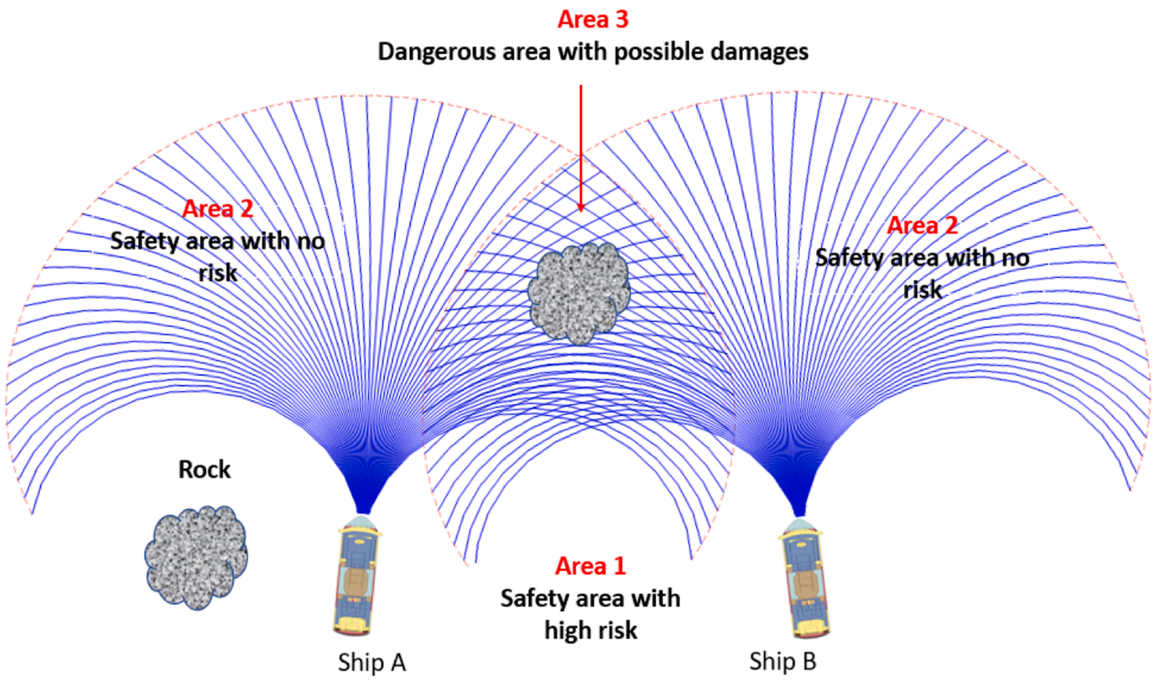


Fig. 2. Decision support for ship collision and grounding prevention in practices.

avoidance action or lowest damage action). More details can be realised within the context of the framework depicted in Fig. 3. At each iteration, the ship manoeuvring simulator aims to determine which of the ship positions (ship dynamics) to extend in advance. The safest avoidance action is achieved by risk analysis and the evaluation of possible damage to determine safe manoeuvring commands. The intelligent decision support system selects safe avoidance actions that minimise $F(t)$. In this case, this system can decide when, where, how, and why to take prevention options in real operational conditions. It also provides the corresponding ship control commands accounting for ship maneuvering characteristics to crews [53].

Fig. 3, displays the key thinking blocks for the collision and grounding assessment of intelligent support systems. Those are:

- An **observer module** that idealises real operational conditions accounting for the complex features of waterways, environmental conditions, traffic scenarios, and ship motions. In this module, the observer should be in a position to denote the data centre to collect big data streams in the time domain, e.g., traffic data - Automatic Identification System (AIS) data, nowcast data (hydrometeorological data streams), bathymetry data, ship manoeuvring characteristics, etc. [47].
- A **risk analysis module** that aims to detect critical scenarios and analyse collision and grounding probabilistic risk in real operational conditions [43,48].
- A **damage (consequence) evaluation module** that is used for the evaluation of the damage extent (or in a broader sense, the consequences of collision or grounding accidents) in the time domain and in real operational conditions, assuming no evasive actions [52,54].
- A **proactive accident prevention module** (rapid predictive methods for the test of manoeuvring commands) that may be used to test and determine the effective collision and grounding avoidance actions (e.g., safe ship manoeuvring commands) using Eq. (1). Based on the time-varying operational conditions and specific critical scenarios, each iteration of potential prevention options is carried out using the ship manoeuvring simulators and the consequence simulators. The safest manoeuvring instruction is selected when the *F(t)* is minimized [53].

Fig. 3 illustrates that the foundational theories for proactive accident prevention and the key components of the intelligent decision support systems for ongoing ships in real operational conditions can be categorized as (1) risk analysis methods, (2) damage evaluation methods, and (3) rapid predictive methods for the testing of manoeuvring commands. Over the past two decades, numerous methodologies and their applications within these domains have been proposed. To elucidate the trajectory of technological advancements within the aforementioned domains, a comprehensive literature review spanning from 2002 to 2023 has been conducted. Particular emphasis has been placed on examining the accompanying techniques and their potential applications in collision and grounding assessment, as they are indispensable components for facilitating proactive accident prevention within intelligent decision support systems.

1.3. Questions and contributions

This study focuses on reviewing the integral components of risk analysis, damage evaluation, and rapid ship motion modelling/prediction methods, which form the foundational loop within an intelligent decision support system. The scope of the study encompasses ship-to-ship collisions and groundings, while collisions involving ships and offshore structures (contacts) are not addressed in this paper. This review is conducted within the specific context of collision and grounding risk mitigation and accident prediction. The primary goal is to provide an encompassing perspective on methodological challenges and the pragmatic applicability of both established and emerging research. The paper endeavours to address the following inquiries:

- What are the trends in global maritime accidents, and what are the underlying purposes or social impacts of preventing collisions and groundings? (Section 2)
- What are the key components of decision support methods for collision and grounding prevention? How do state-of-the-art methods integrate these components, and what methodologies and technologies have been utilized to develop the intelligent decision support systems for ongoing ships in real conditions? (Sections 4, 5, and 6)

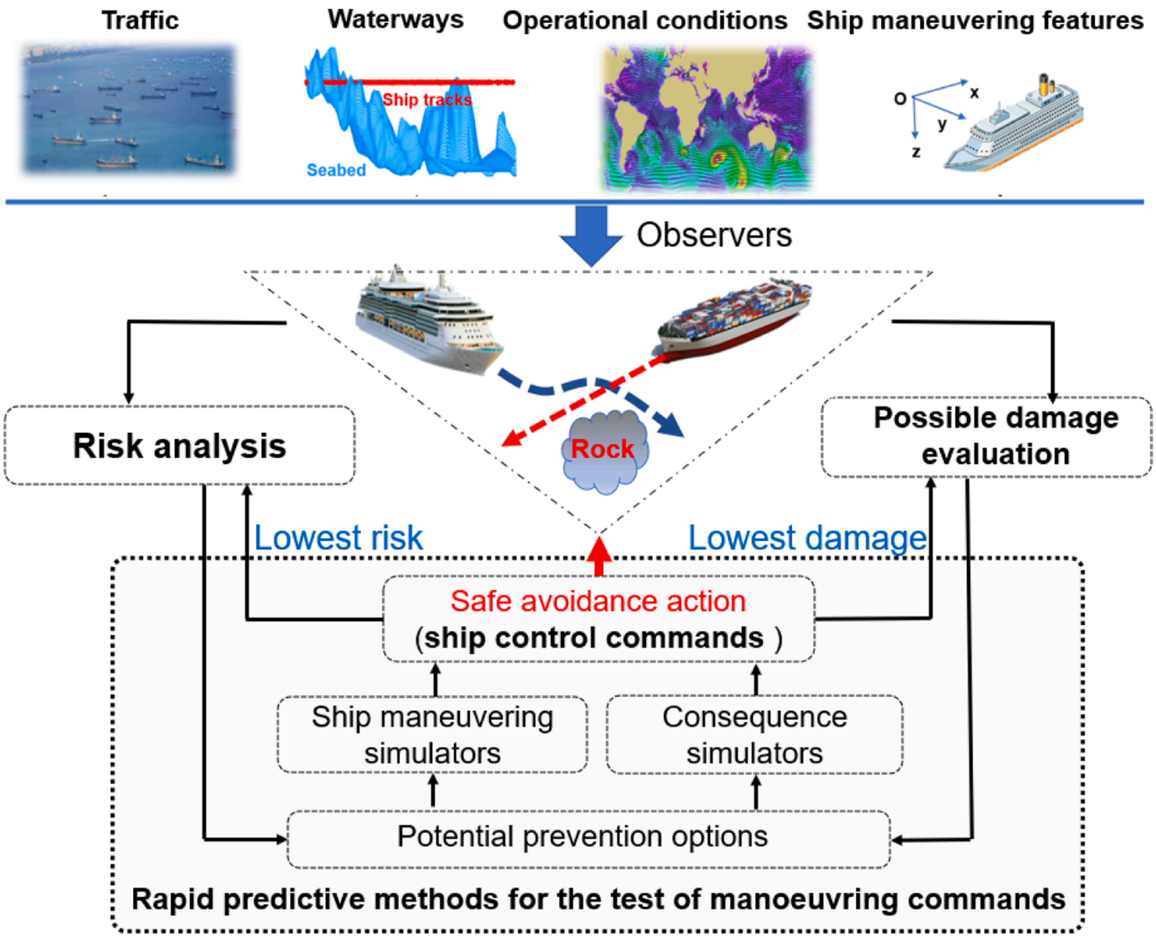


Fig. 3. The main loop for proactive maritime accident prevention of the intelligent decision support system in real operational conditions.

- What are the requirements and trends in technology development that could facilitate the prevention of collisions and groundings in systems driven intelligent decision support systems? (Section 7)

The contribution of the paper can be highlighted as follows:

- Present the trends in global maritime accidents from 2002 to 2022 and highlight the underlying purposes or social impacts of preventing collisions and groundings.
- Provide an updated synthesis of methodologies and technologies used in collision and grounding prevention and evaluate the practical applications and effectiveness of intelligent decision support systems in enhancing maritime safety, focusing on recent technological advancements.
- Identify gaps in the current literature and suggest directions for future research, particularly in the development and implementation of intelligent decision support system technologies of NG-WTS.

The rest of the paper is organized as follows: Section 2 provides a systematic review of maritime accidents. Section 3 elaborates on the methodology of a comprehensive literature survey. Section 4 presents an analysis of risk evaluation methods, followed by an evaluation of ship crashworthiness methods in Section 5 and methods for predicting ship motions in Section 6. The paper concludes with discussions in Section 7 and conclusions in the final sections.

2. Global maritime accident review

In recent years, safety has emerged as one of the foremost priorities within the maritime industry. To delineate the distinctive features and situations of global maritime accidents, an examination of historical accidents on a global scale has been undertaken. The data utilized for this analysis has been sourced from Lloyd's List Intelligence Casualty Statistics,[1] spanning a timeframe of the past two decades.

2.1. Maritime accident statistics from 2002 to 2022

A review of the maritime accident casualty statistics indicates that in the past 20 years (from 2002 to 2022), 55,469 accidents/incidents occurred. There are only 2632 accidents/incidents categorized as minor severity events (labelled as "no serious" in the database), whereas 52,837 are considered significant, severe, or catastrophic events (classified as "serious"), as evaluated by Lloyd's List Intelligence Casualty Statistics. Notably, a significant portion, approximately 95.25 %, of these global maritime accidents are classified as serious accidents. Fig. 4 illustrates the geographical locations and distribution of these global maritime accidents, which have led to significant and dire consequences. Based on accident statistics, these incidents have resulted in the loss of 11,707 lives, injuries to 4204 individuals, and an additional 2992 people reported as missing. Furthermore, 1792 accidents have caused sea pollution or oil spills, and a total of 3287 ships have been lost, whether due to constructive total loss or actual total loss.[2]

[1] https://lloydslist.maritimeintelligence.informa.com/sectors/casualty.
[2] Constructive total loss: the estimated costs for its repair are more than the value of the ship; Actual total loss: a ship is damaged to such an extent that it can be neither recovered nor repaired for further use.

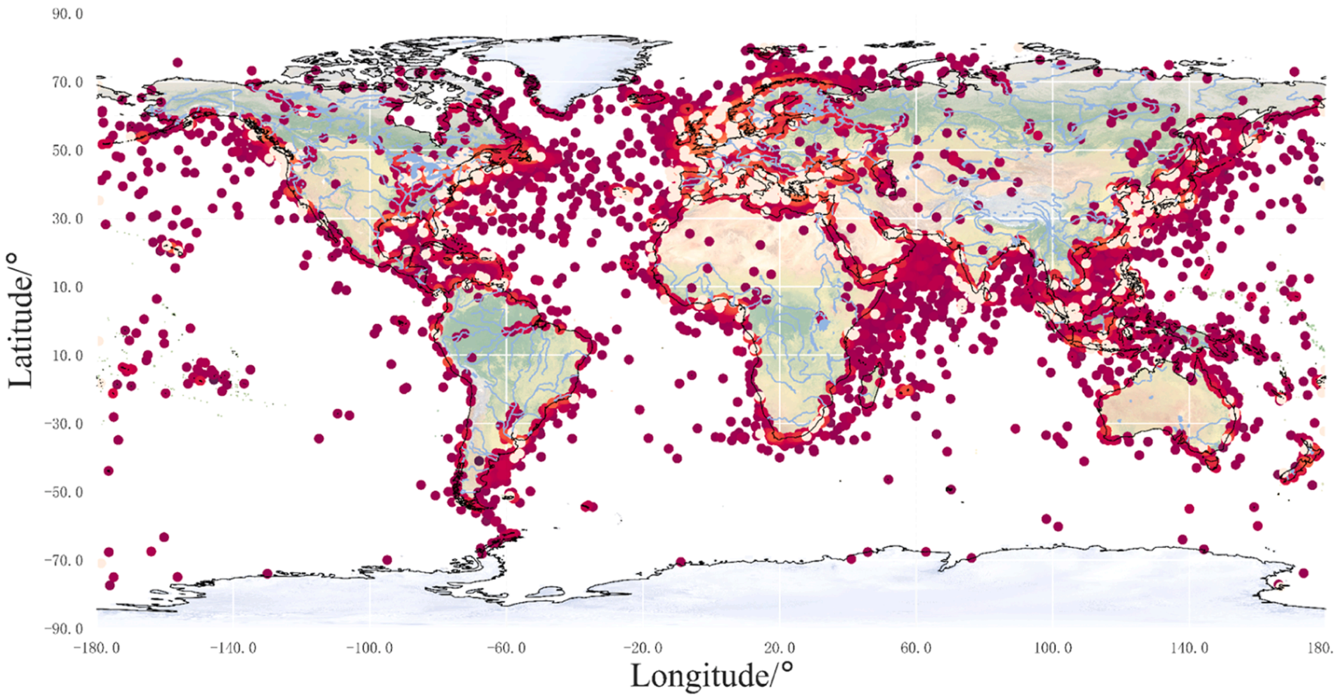


Fig. 4. Statistical review and spatial distribution of global maritime accidents from 2002 to 2022. (Data source: Lloyd's List Intelligence Casualty Statistics).

To further explore the temporal distribution of global maritime accidents, a polynomial equation has been applied and the trendline is generated as displayed in Fig. 5. The green line and scatters denote the number of maritime accidents per year. The red dotted line presents the trendline, and the band represents the 95 % confidence interval of the regression. It is noteworthy that, on a global scale, the number of maritime accidents tends to increase. It is important to note that the number of maritime accidents in 2021 was 1.74 times higher than in 2002, indicating a significant 74 % increase over two decades. However, it is also relevant to consider that the number of ships increased by 1.91 times during the same period. This statistical comparison suggests that, despite the increase in the number of ships, ship safety has not witnessed substantial improvement over the years. Therefore, there is an urgent need for enhanced maritime risk mitigation and accident prevention strategies to improve operational safety under real operational conditions.

These findings underscore the imperative of proactively minimizing human errors, environmental, and asset costs associated with accidents, emphasizing the criticality of fostering a secure and sustainable maritime environment. In essence, there exists a pressing need for the development and deployment of sophisticated tools for proactively preventing maritime accidents. These tools must possess the capability to swiftly detect, comprehensively analyze, and effectively mitigate risks for ongoing ships under real conditions. This proactive approach is pivotal for ensuring the safety and sustainability of shipping practices.

2.2. Characteristics of global maritime accidents

In this section, the initial events are analysed to present the causes of the casualties. Fig. 6 presents the distribution of global maritime casualty events over the period of 2002–2022. The statistical review indicates that ship-to-ship collisions, groundings, and strandings account for 33 % of maritime accidents, making them the most frequent type, as shown in Fig. 6. This significant percentage highlights the prevalence of these types of accidents in global maritime accidents. It is often observed that unsafe ship operations and human errors play significant roles in causing these initial events, suggesting that factors such as misjudgment, lack of attention, and insufficient knowledge or awareness are critical

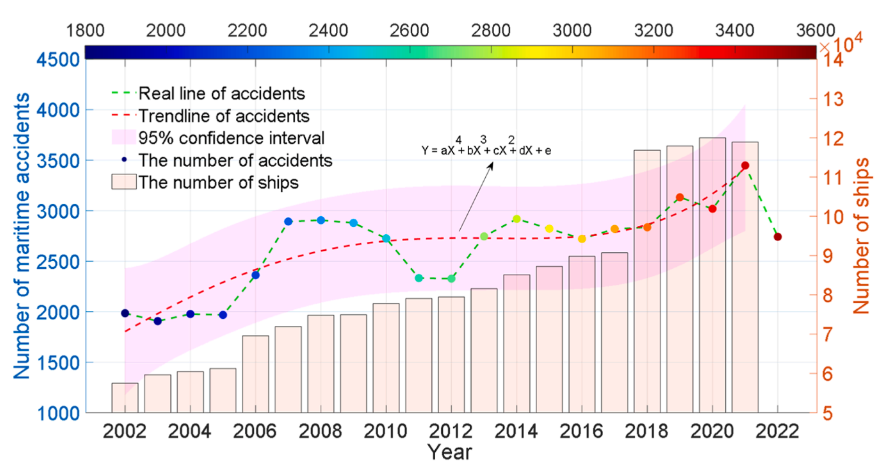


Fig. 5. Temporal distributions of global maritime accidents by year from 2002 to October 2022. (Data source: Lloyd's List Intelligence Casualty Statistics).

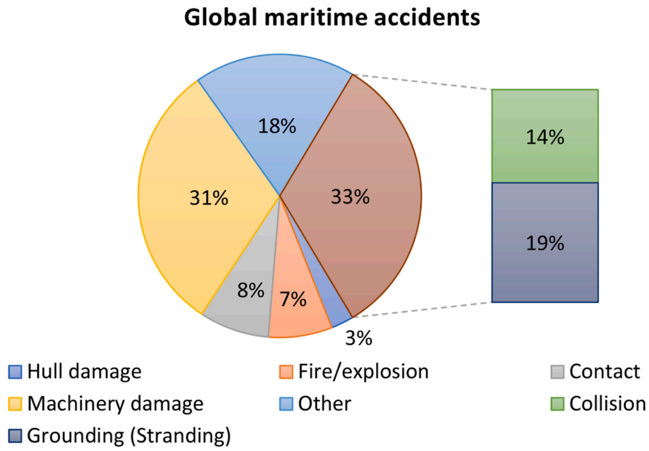


Fig. 6. Distribution of global maritime casualty events over the period of 2002–2022. (Data source: Lloyd's List Intelligence Casualty Statistics).

contributors [34]. This underscores the importance of addressing human factors in intelligent decision support systems to mitigate the risk of such accidents. In addition, the paper reviews the distribution of global maritime casualty events for the different ship types as shown in Appendix A. The results indicate that container vessels, passenger ships, and dry cargo vessels (e.g., bulk carriers) are the top 3 dominated ship accident records. Accident records are taxonomized, and the criteria for classification are shown in Fig. A 1.

The analysis of maritime accidents over the past two decades, reveals a concerning trend in the frequency and severity of maritime accidents (Fig. 4). Despite the increase in the number of ships, the proportionate rise in accidents signifies that the existing measures for accident prevention are inadequate (Fig. 5). Notably, serious accidents constituted over 95 % of incidents, underscoring a pressing need for effective risk mitigation strategies. The predominant causes of these accidents—collision and grounding—highlight the critical role of human errors and technical failures in maritime safety. This situation urgently calls for a detailed review of the existing methods for the development of systems-driven decision support systems for ship collision and grounding prevention. The maritime accidents review indicates that while some methods are in place, they fall short in addressing the complex and evolving nature of maritime risks adequately. A systematic review of these methods is imperative to identify their shortcomings and to innovate more robust solutions tailored to the technical needs of NG-WTS.

Overall, the persistent high frequency of maritime accidents and the identified deficiencies in existing decision support methods necessitate a focused and strategic enhancement of technologies aimed at preventing such incidents. This paper further delves into reviewing existing systems driven decision support methods regarding collision and grounding assessment, reviewing their efficacy, and proposing advanced solutions to meet the exigencies of a new generation of maritime operations, aiming to significantly bolster the safety and sustainability of maritime activities worldwide.

3. Systematic literature review

The Science Citation Index database in the Web of Science (WoS) Core Collection was retrieved as the source for this study. The scope of the review focuses on the topic of collision and grounding assessment, considering three main aspects: collision and grounding risk analysis, damage evaluation, and ship motion for proactive maritime accident

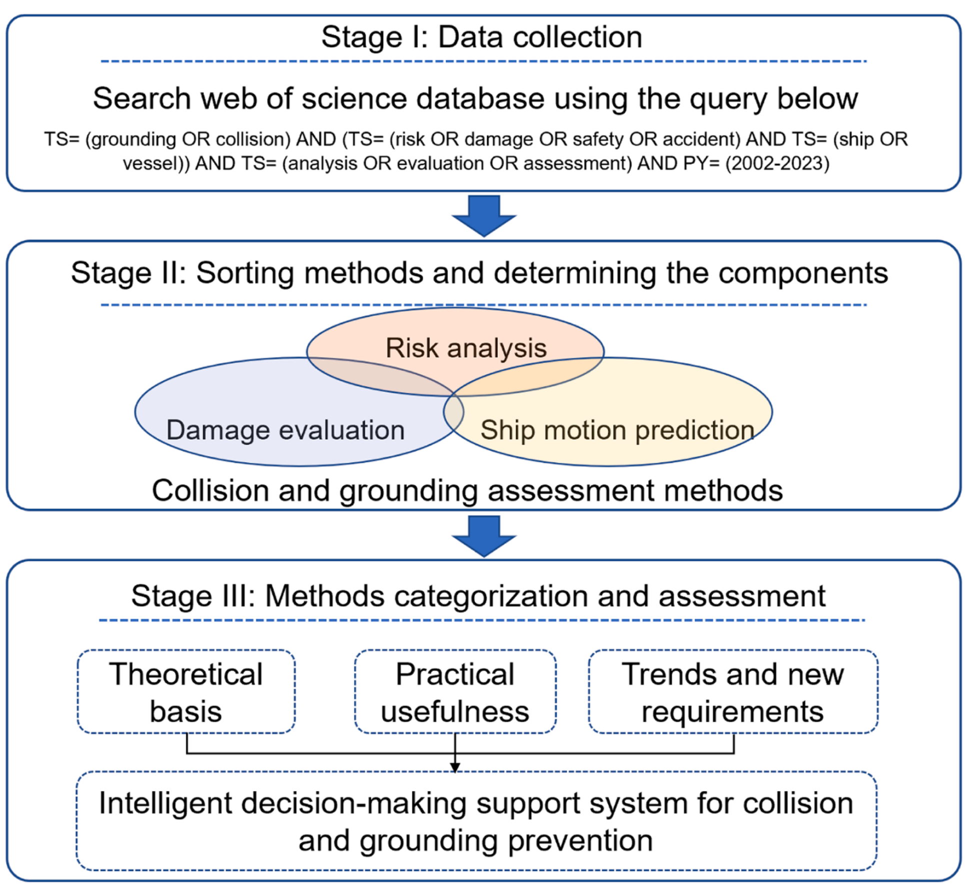


Fig. 7. Stages of systematic literature review and method review.

prevention. Fig. 7 presents the flowchart of the systematic literature review and method review. These stages are summarized as follows:

- **Stage I: data collection**. The literature database is developed by searching the WoS database using the query: TS= (grounding OR collision) AND (TS= (risk OR damage OR safety OR accident) AND TS= (ship OR vessel)) AND TS= (analysis OR evaluation OR assessment) AND PY= (2002–2023). The initial database consists of 1433 journal papers.
- **Stage II: topic browsing and components determination.** Browsing titles, abstracts, and keywords, papers are initially added to the acceptance list, including 654 papers. Subsequently, to categorize the methods and identify the components of collision and grounding assessment, the database from Stage I is refined by concentrating on the query: TS= (risk analysis) OR TS= (damage evaluation OR damage assessment) OR TS= (ship motion prediction). These papers were classified into three sub-databases. There are 560, 270, and 142 papers on risk analysis, damage evaluation, and ship motion prediction, respectively, aimed at proactive maritime accident prevention. There is some overlap among these topics, and studies like this are crucial for analyzing the connections between different components, which is key to developing intelligent decision support systems for ships operating in real conditions.
- **Stage III: paper reviewing and methods categorization.** According to the research questions, a document was recognized as relevant if it presented key methods or theoretical concepts. The breakdown of the categories with the general aim of each method is presented in Table 1. At this stage of dataset preparation, all documents were browsed to verify if they meet the requirements of intelligent decision support systems (see *Figs. 1* and 3) and, if so, these papers were assigned to a suitable thematic category. For each category, the methods are categorized and assessed. The theoretical basis and practical usefulness are analyzed, and the trends and requirements in the technology development of collision and grounding prevention of NG-WTS are highlighted. The final dataset includes 126 papers on collision and grounding risk analysis, 97 papers on ship collision and grounding damage evaluation, and 64 papers on ship motion prediction.

Table 1
The categories of intelligent decision support methods for ship collision and grounding prevention distinguished in the study.

The category	The general aims of the method
Maritime risk and safety management framework	Used to establish guidelines and protocols that enhance maritime safety through risk management strategies, aligning operations with international safety standards.
Static risk analysis	Used to assess risks using historical data and static conditions, providing a snapshot of potential hazards that could lead to collisions or groundings and presenting the corresponding risk control options in a specific sea area or waterways.
Dynamic risk analysis	Used to evaluate real-time data and changing conditions, aiming to predict and mitigate risks dynamically in time domain as they develop during ship operations at sea.
Collision and grounding damage	Used to analyze the extent and impact of damage from collisions or groundings, helping in the development of more resilient ship operation strategies. The methods and scope include probabilistic approach, internal and external mechanics, machine learning methods, and applications on ship operation safety.
Ship motion prediction using mathematical methods	Used to utilize mathematical models to predict ship motions and interactions under various conditions, enhancing the accuracy of navigation and collision and grounding avoidance systems.
Ship motion prediction using AI, DL, ML, etc.	Used to leverage advanced technologies such as AI, DL, and ML to improve predictive accuracy of ship motion predictions and decision-making in dynamic and complex maritime environments.

4. Collision and grounding risk analysis

Collision and grounding risk analysis refer to identifying, measuring, and mitigating risks [55,56]. Most risk analysis methods concentrate on aspects such as shipping management, ship attributes, controlling human errors, and evaluating the navigational environment — either individually or in various combinations [41]. The objective is to identify potential risk scenarios, assess their risk severity, and ascertain the need for preventive measures, including the timing for their implementation. Overall, maritime risk analysis can be classified into three main aspects: (1) maritime risk and safety management framework, (2) static risk analysis, and (3) navigation-related dynamic risk analysis.

4.1. Maritime risk and safety management framework

Maritime safety management aims to enhance ship safety and reduce pollution from ships. This is achieved by the development and implementation of rules, regulations, and safety management systems that aim to assure the highest safety standards. The assurance system is supported by IMO, Classification Societies, ISO standards, and other regional maritime organizations. Maritime risk and safety management is defined by strategic and operational management tools. The former focuses on long-term decision-making and considers risk holistically. The latter aims to support short-term decision-making during ship operations [36].

Most of the studies in strategic safety/risk management for maritime transportation are motivated by the requirements addressed by ISO 31000 [39], the IMO FSA [40] and ISM. Regional risk management frameworks, such as the OpenRisk Guidelines are also motivational in terms of risk management of sea pollution prevention, preparedness, and emergency response at sea [57]. Notwithstanding this, the interpretation of these frameworks and the guidance on risk and safety management seem to be underutilized in practice. This is because it is challenging to suggest reliable risk control options for the end-user during shipping operations.

To address the problem, many studies have been conducted from practical perspectives. For example, work-related to FSA has been introduced [41,58,59]. The study on ISO 31000:2018 [60,61], and the research on HELCOM [62,63] also belong to this category. The focus is mostly on improving regulations. However, there is a lack of emphasis on the underlying safety science and reliability analysis methods that can be used to evaluate navigational risks in real operational conditions.

In literature, many operational risk/safety management regulations have been presented to assist in decision-making during shipping operations. Examples are COLREGs [42,47], and Polar Operational Limit Assessment Risk Indexing System-POLARIS [64]. POLARIS is a standard approach that may be used to determine limitations for ship operations in ice-covered waters [65,66]. All ships should comply with COLREGs to ensure safe operations during encounters [67]. However, these rules underestimate the complex features of waterways and traffic scenarios in real conditions. The master cannot capture all the information from ship dynamics, waterways, traffic, and external operational conditions for accident prevention, which often results in rule violations. The statistics review indicates that 56 % of major collision accidents are caused by such violations associated with ignoring risks under extreme conditions [46].

Recently, novel methods have been used with the aim of quantifying risks identified by COLREGs, such as the quantitative method to represent rules for collision avoidance [68], and stand-on ship responsibility evaluation for conflict elimination [69]. Other studies focus more on traffic conflict evaluation [43,70]. Whereas these studies aim to rank traffic complexity or risk severity during shipping operations, they could practically assist seafarers with the appreciation of the severity of traffic situations only if the environmental conditions, their effects on ship dynamics and associated uncertainties are appropriately accounted for [47,71].

Safety standards or operation frameworks of autonomous ships are also developing. The strategic plan of IMO from 2018–2023 demonstrates the integration of technologies within the context of the regulatory framework is imminent. IMO realise the degrees of ship autonomy [72], as follows: Degree 1: Ship with automated processes and decision support; Degree 2: Remotely controlled ship with seafarers on board; Degree 3: Remotely controlled ship without seafarers on board; and Degree 4: Fully autonomous ship. In recent years, the IMO Maritime Safety Committee (MSC) inaugurated the development of new operational risk/safety management regulations for autonomous ships for entry into force on 1 January 2028. With the latter in mind, this paper discusses practical applications of emerging methods to achieve Degree 1 autonomy for ships (see Sections 4.2 and 4.3).

4.2. Static risk analysis methods

Static risk analysis methods aim to identify, measure, and mitigate risks from a macro perspective. They may be used to identify the risk factors, quantify a risk situation, and provide the corresponding risk control options in a specific sea area or waterways [73].

Many static risk analysis methods and applications have been presented, taking human factors, ship features, environmental factors, and organizational factors into account. To date, review papers present the rationale for the most influential models/methods with focus on collision risk analysis [7,19,74]. Various review papers discussed the potential use of science-based risk analysis models for the estimation of the probability of ship grounding risk [22,75,76]. Notable, the applicability of risk models to autonomous ships was further discussed [77].

Static risk analysis methods can estimate both the probability and the consequence of collision accidents from statistical and analytical perspectives. Most of them are based on historical accidents, traffic records and expert judgment. They can be divided into nine categories based on the modelling techniques, and details about the stipulation of the theoretical basis and practical usefulness are presented below. Fig. 8 presents the trends of types of studies done across the years between 2002 and 2023.

(1) Bayesian network models

Bayesian networks (BNs) are graphical methods that can be employed to represent joint probability distributions of undesirable events. They offer a convenient and coherent tool for illustrating the uncertainty of complex systems and are increasingly utilized for risk analysis and reliability assessment based on uncertain knowledge. They have been employed to quantify the probability of causation in specific areas such as ship collisions [78–80] and groundings [81,82]; see an example of BNs model in Fig. 9. The effective utilization of BNs requires careful consideration of several critical factors, particularly in the context of a complex maritime transportation system [83]. This stems from the fundamental reliance of the network's accuracy on the availability of ample, high-quality data for appropriate parameterization. Inadequate or subpar data can introduce biases and compromise the reliability of the resulting analyses. Furthermore, the outcomes of a BN analysis are notably influenced by the selection of initial probabilities and assumptions established during the formulation of the model. These choices can exert a significant impact on the validity of the obtained results. While BNs excel at capturing dependencies among variables, their ability to encompass intricate causal relationships within specific systems may be constrained. This underscores the need for a prudent interpretation, acknowledging that certain nuanced cause-and-effect connections may not find complete representation within the structure of the network [84,85].

(2) Fault tree and event tree models

Fault Tree Analysis (FTA) is a systematic method used to analyze the potential failure modes within a system and understand the causes and consequences of these failures. In the context of safe ship operations, FTA would involve identifying the various potential fault scenarios that could lead to a collision or grounding incident [86]. Event Tree Analysis (ETA) is a complementary method to FTA. It focuses on the potential outcomes or consequences of specific initiating events identified in the fault tree. Once the initiating events that could lead to a collision or grounding are identified in the fault tree, an event tree would be constructed to explore the sequence of events that follow these initiators. This helps in understanding the potential outcomes of the accidents, including ship damage, oil spills, environmental impacts, and human casualties. Fault Tree (FT) and Event Tree (ET) have been used to illustrate accident processes and their consequences on safe ship

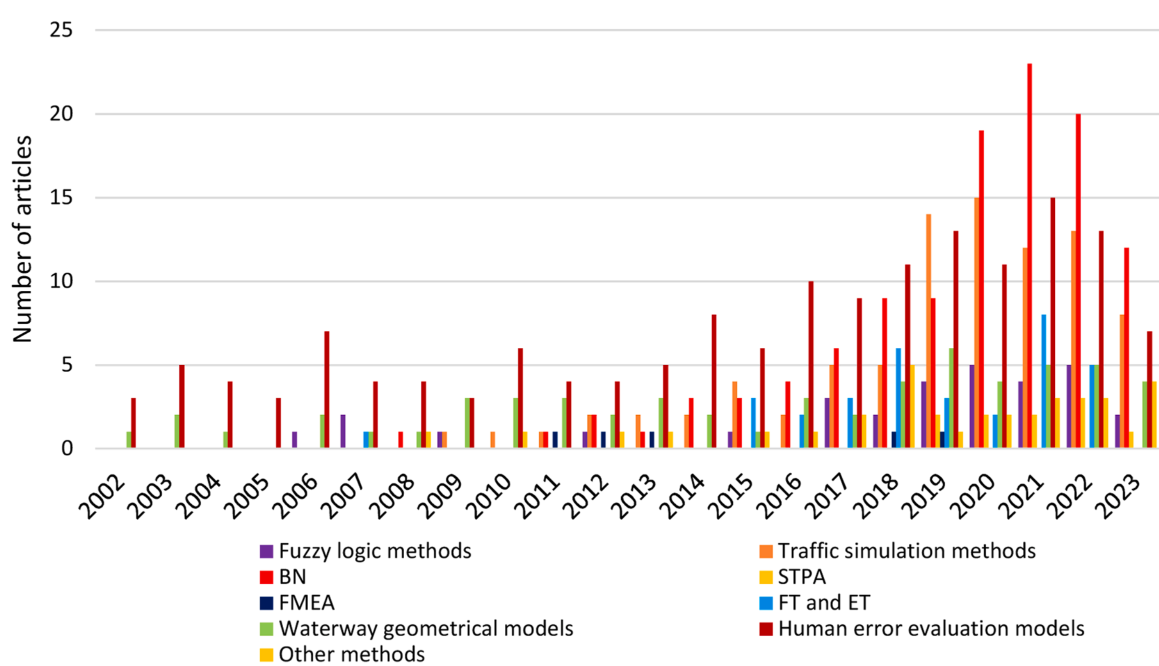


Fig. 8. The distribution of articles of different studies in collision and grounding risk analysis by year of publication.

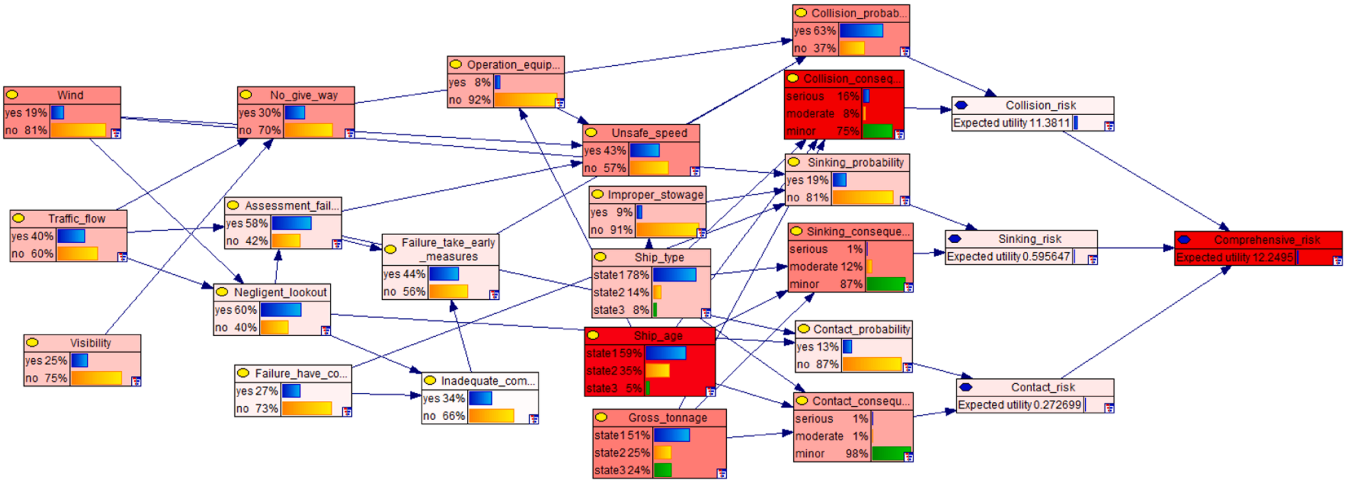


Fig. 9. Bayesian networks model for maritime risk analysis [134].

operations following collisions [87–89] and groundings [90,91]. These methods present the collision and grounding risk factors and the accident process based on causation theory. Overall, FTA and ETA are valuable tools for risk assessment and management in maritime operations, allowing stakeholders to better understand the complex interactions between factors that can lead to accidents and develop strategies to enhance safety and minimize potential consequences [92].

(3) Failure Mode Effect Analysis

Failure Mode and Effect Analysis (FMEA) is another powerful method used to evaluate potential failure modes within a system or process and understand their effects. In the maritime context, FMEA can be employed to identify the failure modes and potential consequences associated with ship collisions and groundings. It's a systematic and proactive approach that helps in assessing and mitigating risks before they lead to accidents. FMEA is a structured technique used to analyze and prioritize potential failure modes of a system, process, or product. It involves identifying potential failure modes, assessing their effects, and assigning a risk priority based on factors like severity, occurrence, and detectability. By systematically evaluating failure modes and their consequences, FMEA helps in identifying areas where improvements or preventive measures are needed. In the context of ship collisions and groundings, FMEA would involve identifying the potential failure modes that could lead to such incidents. These failure modes could include equipment malfunctions, human errors, navigation system failures, adverse weather conditions, and more. Each failure mode is evaluated in terms of its potential consequences (such as ship damage, oil spills, and environmental impact), how likely it is to occur, and how easily it can be detected or mitigated. For example, a fuzzy FMEA model was proposed for risk evaluation of ship collisions [93]. The FMEA-based approach was developed for maritime risk evaluation [94]. In both cases, FMEA serves as a proactive method to systematically identify, analyze, and prioritize potential risks associated with ship collisions and groundings. This approach allows for the development of targeted risk mitigation strategies and improvements in operational procedures to enhance maritime safety.

(4) Fuzzy logic methods

Fuzzy logic methods may help humans make decisions for a complex reality. It is a mathematical framework that allows for the representation and manipulation of imprecise or uncertain information. It uses fuzzy sets to capture degrees of membership, enabling a more nuanced representation of data that isn't strictly binary (true or false). This is particularly useful when dealing with complex systems where precise numerical values may not be available or applicable. It is adopted when it is useful to recognise, represent and interpret a system within the context of complexity and associated uncertainties. Fuzzy logic methods are applied in various aspects of maritime operations, including decision-making, collision risk assessment, collision avoidance strategies, and more. For example, a fuzzy logic-based multi-attribute decision-making method was proposed for prioritizing maritime traffic safety influencing factors of autonomous ships manoeuvring commands [95]. A fuzzy logic method was developed to quantify the ship – bridge collision risk [96]. The fuzzy logic-based simulation system was designed to address the collision avoidance issue using the dynamic predictive guidance technique [97]. The systematic literature review of fuzzy logic methods used in maritime risk analysis indicates that the method is often applied in static and dynamic risk analysis.

(5) System-Theoretic Accident Model and Processes

The Systems Theoretic Process Analysis (STPA) is a comprehensive and structured hazard analysis method used to identify and understand complex safety and risk issues within systems [98]. STPA goes beyond traditional hazard analysis techniques by considering not only individual component failures but also systemic factors that contribute to accidents and incidents [99]. It was developed as an extension of the Systems Theoretic Accident Model and Process (STAMP), which focuses on the underlying control structure and dynamics of systems [100]. It was introduced by Leveson (2016) [101]. Recently, this framework has been adopted in maritime risk analysis [102,103]. For example, a method was developed to evaluate risk control actions for the collision avoidance process using the STPA model [104]. An STPA-based model was developed to elaborate a systemic and systematic hazard analysis for autonomous ships from the earliest design phase [105]. Furthermore, a new method was proposed by integrating STPA and BNs to enable supervisory risk control for autonomous ships [106,107]. This study focuses on the possible system hazard identification of autonomous ships, trying to prevent the manifestation of hazards and consequently accidents.

(6) Maritime traffic simulation tools

Maritime traffic simulation methods aim to capture the traffic features and simulate ship traffic for probability evaluation of collision and grounding [108]. Traffic simulation models have been developed to evaluate the probability of collision occurrence [109,110] and grounding [76,111]. These methods rely on historical traffic records and are difficult to extend for probability evaluation in the future. To extend maritime traffic simulation methods, a data-driven model was proposed for risk analysis of ship collisions with stationary infrastructure using AIS data and a ship manoeuvring simulator [108]. The methodology integrates modern simulation and analysis tools. Based on this work it is suggested that simulations can be used to identify scenarios (e.g., drifting, or sharp turning and/or miss of turning point during shipping operations) that may lead to accidents. The models are linked with AIS data, to calculate the probability of ship collisions. The paper presents event statistics used in the scenarios, simulation setup, case study area, and results and discussions of the analyses. The conclusions highlight the applicability of the methodology and its potential for future research.

(7) Waterway geometrical models

Waterway geometrical models are established based on real operational conditions of traffic flow (Fig. 10). These approaches often involve fitting traffic flow distributions from various waterways using Normal and Poisson distributions. Consequently, collision probability can be computed by identifying overlapping regions among traffic flow distributions [112,113]. Similarly, grounding probability can be determined by identifying intersecting areas between traffic flow distributions and shallow waters [48,114]. Comparison studies have been conducted by COWI [115] and Silveira [116]. The probabilities of collision and grounding reflect the complexity of the waterway, and these overlapping areas serve as alert zones for ships. These methods primarily consider the current traffic flow distributions, rather than quantifying collision and grounding risks by analysing the geometric relationship between ships. However, it should be noted that collision and grounding probabilities are quantified under the assumptions that (1) traffic flow conforms to existing distributions, and (2) the effects of environmental loads on ship traffic in the spatial-temporal domain are disregarded.

(8) Human error evaluation methods

Human error evaluation methods play a crucial role in preventing collisions and groundings within maritime transportation systems [34, 117]. These methods shed light on the potential impact of human actions, decisions, and behaviours on accidents and incidents [118]. The notional inclusion of human factors may contribute significantly to improving safety and reducing the risks associated with maritime accidents (collisions and groundings) [119]. Available approaches can be taxonomized as "human error identification methods" and "human error probability assessment methods". To identify human errors various techniques such as (a) the Cognitive Reliability Error Analysis Method (CREAM) [120], (b) the Human Error Assessment and Reduction Technique (HEART) [121], (c) the Human Factors Analysis and Classification System (HFACS) [122], and their evolutionary models [123] are used. The use of Bayesian Networks (BNs), Fuzzy Logic, and Evidential Reasoning is transcendental and with the focus on evaluating the probability of human error. Examples include BNs-based CREAM [124], Fuzzy Logic-based CREAM [125,126], Evidential Reasoning-based CREAM [127], Fault Tree-based HFACS [128], Fuzzy BNs-based HFACS [129], and others. Human error evaluation methods provide valuable insights and tools for preventing collisions and groundings in maritime transportation. Collectively, these methods contribute to the improved understanding of human factors and systemic influences. This enables stakeholders to proactively address potential vulnerabilities, enhance safety measures, and promote effective risk management strategies. Nonetheless, the implementation of thorough human error evaluation methods often necessitates a substantial commitment of time, labour, and resources. This encompassing process could entail the training of personnel, the compilation and meticulous analysis of data, and the maintenance of essential software or tools. Unfortunately, these demands may not always align with the practicalities of ongoing ship operations. Furthermore, it's important to note that many human error evaluation approaches adopt a retrospective approach, delving into past incidents or accidents to unearth factors linked to human actions [130]. Regrettably, this retrospective nature diminishes their applicability for real-time monitoring and immediate intervention within the context of ongoing ship operations. While these methods prove adept at recognizing historical patterns of human error, their capacity to precisely forecast future instances may be limited. This limitation consequently undermines their efficacy in pre-emptive prevention efforts [34]. Therefore, the intelligent decision support system can be an alternative to improve the human-based decision-making system, supporting to mitigation of human errors for ongoing ships [95].

(9) Other emerging methods

In addition to the methods, as mentioned, there are several other emerging methods and technologies being applied in collision and grounding risk analysis. These methods often leverage advancements in data analytics, simulation, and automation to enhance safety and mitigate risks. The Analytic Hierarchy Process (AHP) method is used for maritime risk analysis with the focus on human error. The error bands are based on questionnaires and accident records. It has been applied in several studies, including the analysis of grounding accidents caused by human error [131], the evaluation of the probability of human error in transporting steel cargo with bulk carriers [132], and the assessment of the impact of human factors on the safety of pilotage operations [133].

Regression is a field of Machine Learning (ML). They aim to predict the collision and grounding risks by training a regression model using expert knowledge or historical records. Regression methods have been applied in collision risk prediction, the nature is to capture the nonlinear relationship between the collision risk and its influencing factors (i.e., distance, ship speed, bearing angle, etc.) [135]. Additionally, a risk analysis model for near-miss ship collisions was proposed using the logistic regression [136]. The proposed model was trained to consider the Closest Point of Approach (CPA) and collision avoidance variance, which was used to identify near-miss ship collision scenarios. These methods have the potential to predict the grounding risk and collision risk, but they are very sensitive to the training data and data generation model.

Conclusions obtained from the existing studies and the static risk analysis studies were carried out based on small sample datasets (traffic flow, expert knowledge, and accident records), which also involve some assumptions. They assume that (1) the maritime transportation system is static and holonomic in a specific area; (2) the impacts of risk factors on collision and grounding risks can be captured and quantified based on small samples of maritime accident reports. Based on these assumptions, static risk analysis methods are widely applied to busy waterways and

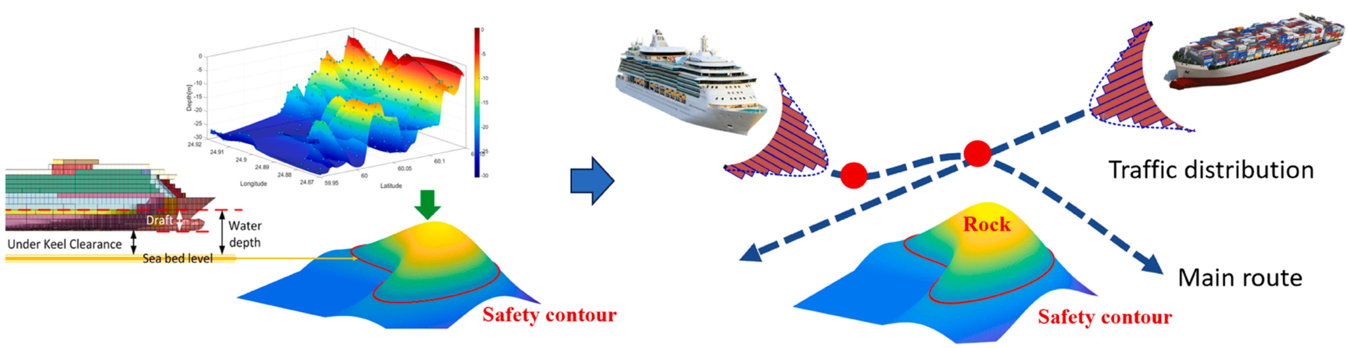


Fig. 10. Waterway geometrical models for the evaluation of collision and grounding risks.

some typical maritime accidents.

Based on the studies of BNs modelling, most studies consider ship features (ship type, ship lengths, ship age, etc.), environmental conditions (wind, wave, and current, etc.), human errors and organizational factors to establish the BNs model and calculate the conditional probability table. The researchers presumed that the environmental factors might influence the consequence and probability of collision and grounding, but the mechanism of influences has not been explained or tested. Therefore, from a macro perspective, the developed BNs models can be used to evaluate the relative overall risk level of collision and grounding for a specific area [85]. The AHP method also has the same features. For causation theory models, such as FT, ET, and FMEA, can be used to present the process of maritime accidents and determine risk control options (RCOs) and are useful for the designation of rules or standards [87]. However, based on several accident cases, they underestimate the big data and are difficult to provide convincing RCOs for the ongoing ships in real conditions. Maritime traffic simulation tools and geometrical models are useful for determining the high-risk areas in a specific area, which can provide warning areas for collision and grounding prevention [76,109,110], but a global simulation tool has not been established. These methods can handle big traffic data. However, they are sensitive to the variable traffic flow and often ignore the environmental conditions [47,48]. STPA is useful to elaborate risk factors from the maritime transportation system of ship systems, which can be used to enhance the resilience of ship systems and maritime transportation systems. There are too many regression tools in the field of ML. These methods have the potential to learn the trends from big data streams. Regression methods are promising to capture the mechanism and features of the coupling among the risk factors using big data. The existing methods are limited by big data.

Overall, static risk analysis models/ methods can be applied to evaluating collision and grounding risk (including human errors) and identify the high-risk area or factors for a specific scenario from a macro perspective, which may provide potential theoretical guidance to traffic managers and policy makers. Notwithstanding this, most of these studies do not consider the dynamic information, such as the time-varying traffic, sea conditions and bathymetry map. They fail to detect the risk scenarios and provide reliable risk mitigation options for ongoing ships operating in real environmental conditions.

4.3. Dynamic risk analysis methods

The dynamic risk analysis methods aim to detect and measure risk for ongoing ships. Dynamic risk analysis models are used for evaluating and identifying collision and grounding scenarios and for providing decision support in determining the timing of evasive actions. Recently, several review papers have reviewed available models addressing dynamic collision risk models and the detection of non-accidental scenarios [19,74,137]. Most of these studies regarding dynamic risk analysis models are based on AIS data. The dynamic risk analysis methods can be categorized into five categories from a theoretical basis. Fig. 11 presents the trends of studies over the past 20 years.

(1) The closest point of approach

The Closest Point of Approach (CPA) is used to present the spatial-temporal relationships between two ships that are employed to represent the collision risk of two ships. CPA includes two indexes: Distance at CPA (DCPA) and Time at CPA (TCPA) [98]. The former denotes the closest distance between two ships, and the latter denotes the time left to arrive at the CPA point. Notably, CPA represents the spatial-temporal relationships between two ships under the assumption that the involved two ships keep their speed and course. Therefore, the CPA also can represent whether the ship takes evasive actions. By setting risk criteria, CPA often is used to detect critical scenarios for ongoing ships. When the dynamic values of TCPA and DCPA are smaller than the risk criteria, the warning alert will be activated [138]. In recent years, various combination methods of TCPA and DCPA were proposed with kinematic status (i.e., relative speed, bearing angle), distance, etc. [139–141]. More details regarding applications can be found in these studies [43,142–144]. Overall, the CPA is the most popular method in the practices of risk analysis. However, among the literature, the weakness is twofold: (1) They underestimate ship motions in real operational conditions and lack commonly accepted risk criteria; (2) The simplified assumptions limit model feasibility. These issues may result in erroneous collision risk detection and underestimate collision risk scenarios in real operational conditions.

(2) Ship domain

The 'ship domain' is defined as a safe space around the ship [145]. The forms and shapes of the ship domain may be defined in different ways. Fig. 12 summarizes typical ship domains and their applications. For example, the study presented a fresh perspective on the definition of ship domains via a comprehensive analysis of AIS data [146]. The study revealed that the ship domain can be conceptualized as an elliptical shape. The size of the region used to capture ship intersections and the influence of water depth were identified as two critical factors. Contrary to existing research findings, it was concluded that the length of the ship does not play a role in determining ship domain characteristics. Potential collision scenarios can be identified by detecting the overlap of such an area, and the collision risk also can be calculated by quantifying the area of the overlap [69]. Typical ship domains and their applications for the evaluation of collision risk have been presented, as shown in Fig. 12. The review paper [147] presents the rationale of the most influential models/methods. Most of the relevant studies focus on collision risk analysis and some on grounding risk analysis [148]. However, the form and shape of the ship domain are extremely dependent on ship

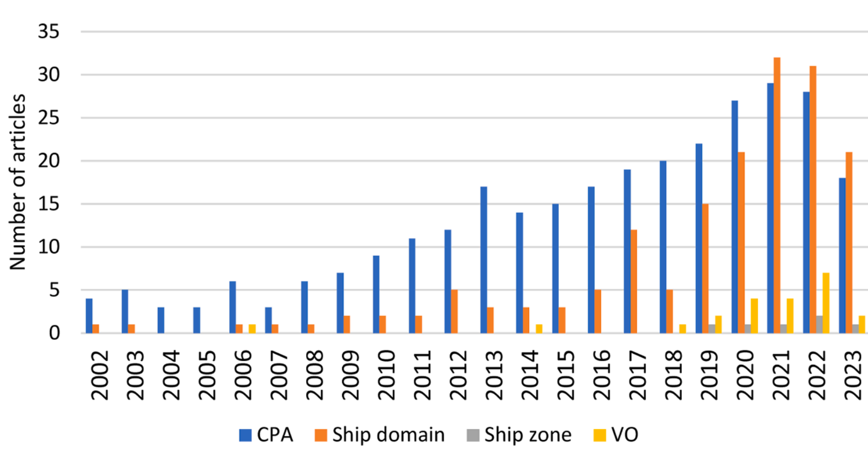


Fig. 11. The trends of studies between 2002 and 2023 (The hybrid methods are classified into the independent method).

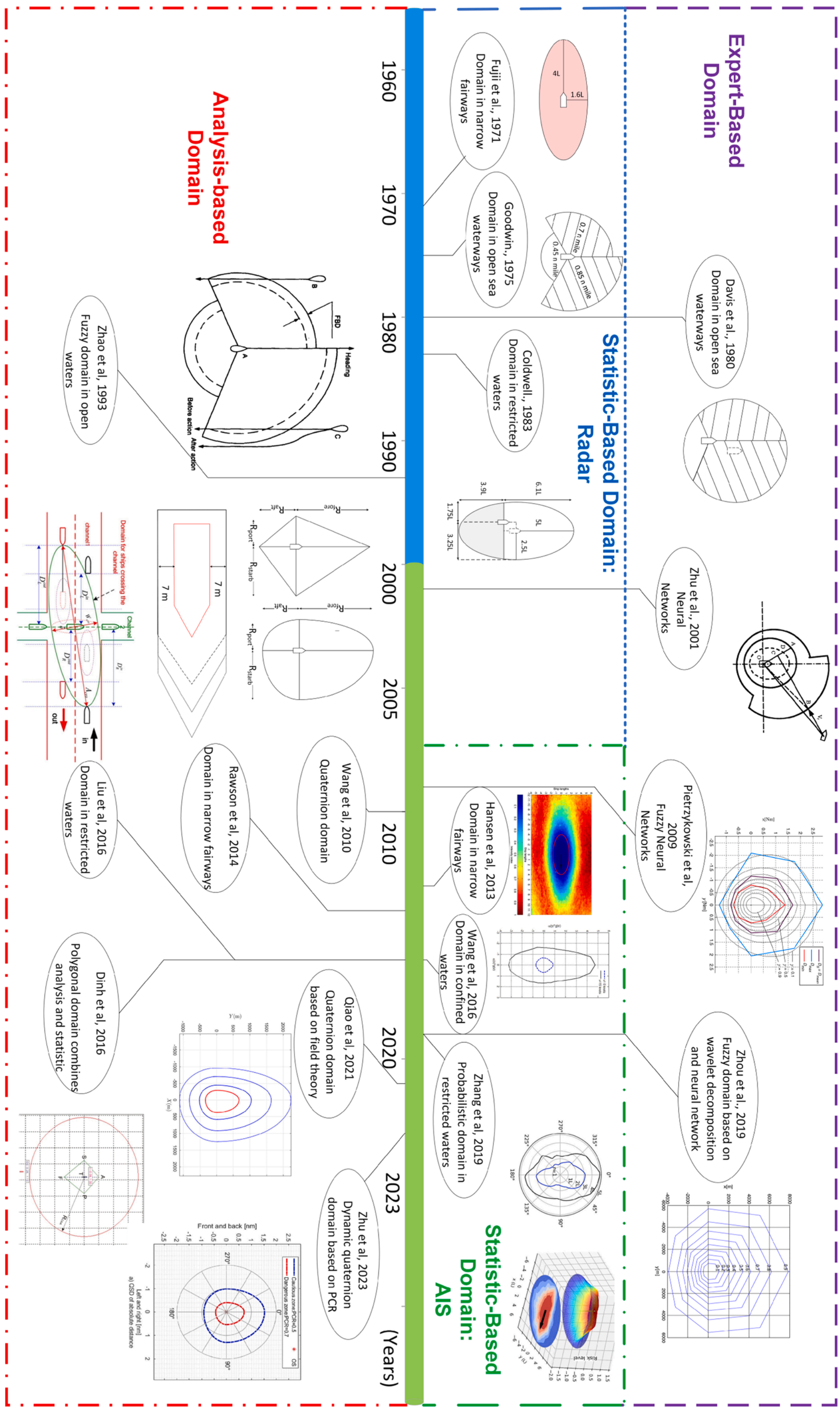


Fig. 12. Ship domains and their application.

manoeuvrability, traffic density, environmental conditions, etc. The initial ship domain and inconsistent definition may underestimate the time-varying ship traffic, operational conditions, and complex ship features. Such approaches may result in warning errors and missing critical scenario detection [146].

(3) Ship zone (Collision Avoidance Dynamic Critical Area)

The 'ship zone' is similar to ship domain but is calculated by determination of a required manoeuvring area considering the dynamic nature of ship operations [149–151]. It considers the features of ship manoeuvring to determine the critical distance to the ship or static obstacles (i.e., rock, shallow waters). It is applied based on a ship manoeuvring solver (a complex ship manoeuvring model) for a RoPax ship [151]. The method can be used to determine the minimum distance to collision and grounding, which is an important safety indicator to enhance safety [43,150]. However, the method is based on a mathematical model of ship manoeuvring, which will be time-consuming to generate the results. In addition, the method ignores operational disruptions, such as the interaction of ships, environmental conditions, and shallow waters. These may limit the feasibility. The accuracy of critical distance is questionable. This is because the size of the critical area is simulated by the ship manoeuvrability model. Therefore, the method can be further improved by using higher accurate ship manoeuvrability model or emerging technologies related to ship motion prediction and ship manoeuvring system identification.

(4) Velocity obstacle method

The Velocity Obstacle (VO) method aims to show the Collision Threat Parameter Area (CTPA), considering the spatiotemporal proximity between two moving obstacles in velocity space [152]. For two moving obstacles, such as two ships, the distance and velocities are shown in the velocity area of obstacle A. Accordingly, the velocity area may be a CTPA, where a collision is possible if obstacle A takes the possible velocities in that area [152]. This method has been extended to the ship collision risk fields. The VO-based model was proposed to measure ship collision risk and prevent CTPA, assuming that the ships do not change their sailing status (i.e., maintain speed and course) [153].

To meet the requirements of maritime practice, many studies have been proposed, such as nonlinear VO [154,155], generalized VO algorithms [156], and probabilistic VO [157]. These methods have been applied to collision risk analysis [158,159], collision probability [152], and potential collision event detection [160]. Notably, a novel VO-based method was proposed to support collision avoidance for autonomous ships [161]. In this study, VO is used to determine the timing for triggering collision evasive actions. Based on the fundamental theories of VO mentioned in the above studies, it was observed that the method could be used in cases involving two moving obstacles, so it cannot be adopted for grounding risk analysis. Additionally, VO underestimates ship motion features in real operational conditions, which may result in errors in collision risk analysis and critical scenario detection.

(5) Hybrid methods

Researchers often combine some of the above-mentioned methods/models to perform collision and grounding risk analysis, such as the Vessel Conflict Ranking Operator (VCRO). The hybrid method was proposed to detect potential collision events and evaluate collision risk using AIS data, combining ship domain and CPA [162,163]. The combination of VO and ship domain was used to analyze real-time collision risk [159,164], considering evasive maneuvers and perceived collision risk. Additionally, a comprehensive big data analytics method was proposed to detect potential collision scenarios and evaluate collision risk during evasive actions taken based on CPA, distance, and ship domain [165]. The study determined commonly accepted collision risk criteria in real operational conditions and validated the differences in complex traffic scenarios in various voyages. For multi-ship encounters, a probabilistic conflict detection approach has been proposed to estimate the potential collision risk in various multi-ship encounters, by combining ship motion and CPA. This approach effectively incorporates the spatiotemporal-dependent patterns of ship motions, thereby achieving accurate predictions of collision criticality in complex environments [165,166]. In addition, a multi-scale collision risk estimation approach has been developed to capture maritime traffic conflict patterns across diverse spatial scales within a specified water area, and the method combines a Fuzzy Clustering Iterative (FCI) method and improved CPA. This proposed method leverages complex network theory and incorporates a graph-based clustering technique to precisely quantify interactions and dependencies among multiple ships [167].

(6) Technical failures on the risk of collisions and groundings

The significance of technical failures and their contribution to the risk severity of grounding events is highlighted in maritime accident reviews (Section 2). From a system reliability perspective, failures in critical ship systems, encompassing engines, propulsion systems, electrical systems, and navigation equipment, can have grave repercussions [168,169]. These failures often culminate in collisions [170] and groundings [171]. The risk of grounding and collision is notably associated with operational scenarios involving drifting ships, carried by waves, wind, and currents while rendered incapable of activating their engines [172]. Other critical scenarios may involve abrupt ship turns caused by malfunctioning rudders, resulting in a fixed rudder position that steers the ship sharply to either port or starboard. Studies on abnormal ship motion behavior detection may be useful to identify drifting ships, sharply turning ships, and missed turning point cases for collision risk evaluation [108,173].

Overall, the prevention of collisions and groundings resulting from technical failures in critical ship systems requires a multifaceted approach. Regular maintenance and inspections, crew training, and the incorporation of redundancy systems are paramount. Leveraging advanced monitoring technologies and emergency response plans can aid in early anomaly detection and effective crisis management. Ensuring accurate navigation, weather-conscious route planning, and regulatory compliance further enhance safety [171]. Open communication, continuous improvement, and proactive risk assessment contribute to a comprehensive strategy for minimizing technical failure-related risks. Through these measures, maritime operators can safeguard ships, crew, and the environment, reducing the potential for accidents and enhancing overall operational reliability [87]. The final objective of these studies is to delve into the underlying causes and consequences of these failures, highlighting the importance of effective maintenance, vigilant monitoring, and preemptive measures in mitigating risk.

Based on the critical review of risk analysis methods, it was observed that most studies of dynamic risk analysis focus on collision scenarios, with only a very small number of studies addressing grounding issues. This development is extremely uneven compared to the number of collision and grounding accident records. In addition, similar to static risk analysis models, dynamic risk analysis models could underestimate collision risk indices as they ignore real environmental conditions, voyage uncertainty, and ship motion features [145,174,175]. Therefore, a new theoretical framework should be developed for collision and grounding prevention. This framework can be used to provide accident prevention actions that reflect hydrometeorological conditions, considering ship dynamics and their consequences.

5. Collision and grounding damages evaluation

Ship damage evaluation models are useful for calculating crashworthiness and potential damage extents, with the goal of minimizing potential consequences, particularly in situations where collision and grounding are inevitable [176,177]. Therefore, these methods can be employed to assess the possible consequences of various ship avoidance actions in order to reduce potential penetration and damage lengths [178,179]. This forms a key component of the intelligent decision support system, as illustrated in Fig. 3.

To date, various methods have been employed to conceptualize ship accident scenarios (e.g., finite element analysis, empirical studies, experimentation, and analytical approaches) [179–182]. Traditionally, external and internal mechanics govern ship collisions and groundings. External mechanics refer to the ship's 6-DoF rigid body motion as influenced by external activities (e.g., added inertia and damping effects due to ship motions, evasive motions following a maneuvering path, kinetic energy of the ship, and external forces such as waves, wind, and currents). The contact between the ships (collision) or the ship hull bottom with hard rock or seabed (grounding) causes energy to dissipate during a collision and grounding accident [183–185]. This causes structural deformation. The study of the structural response (e.g., the resistance of plates, stiffeners, bulkheads, girders, and floors in contact with rock) leading to energy dissipation after the contact is referred to as internal mechanics [186,187]. A summary of assessment methods for ship collisions and groundings is demonstrated in Fig. 13.

(1) Probabilistic approach

The probabilistic risk evaluation (see Sections 4.2 and 4.3) comprises of methods used for the estimation of probabilities of accidents from traffic distributions, historical databases, and associated hazards. Generally, probabilistic statistics are relevant to ship structures created in the past. It is hard to make forecasts about the future using probabilistic statistics [182,188]. Therefore, numerical models that show the physics of the accidental scenarios are of key importance for the future identification of suitable risk control options [189]. Some of the key methods that may form the basis of probabilistic evaluation methods are summarised below.

(2) Internal and external mechanics

Analytical methods employed in the deterministic evaluation of structural crashworthiness often use the upper-bound theorem to calculate the energy dissipation of key structural components (such as plates, stiffeners, webs, floors, girders, etc.) [190,191]. This technique produces accurate predictions of deformation forces and is computationally efficient [192,193]. For evaluating structural member failures in ships, a variety of analytical formulations are available [194–197]. FEM (Finite Element Method) is the most widely used and reliable structural response evaluation method [198–200]. To date, large- and small-scale experiments have been carried out [201–205]. Still, most of the crashworthiness assessment methods are done using FE analysis [189,206].

External mechanics are addressed using a decoupling technique, which ignores the impact of ship motions on structural deformation [207]. This is opposed to the coupled approach, which takes into consideration the ship's 6-DoF rigid body motion as well as the hydrodynamics of the environment (such as additional inertia, damping effects from ship motions, evasive motions following a maneuvering path, and external forces like waves, wind, and currents).

Explicit numerical simulations (e.g., FEM) may be exceptionally time demanding. This is because these models need to be redefined to adequately consider the crushing mechanism using reduced-order models [21,27]. Simplified Element Method (SEM) methods have been proposed [181]. On the other hand, super elements can be used to model ships with very large structural units and determine the closed-form analytical formulations of the resistance of each unit [51,208,209]. Accordingly, the dimensions of ship damages can be rapidly calculated by properly combining the individual resistances. Such methods can pave the way for developing a rapid method for evaluating ship collision and grounding damages in time-varying traffic situations. For example, Zhang et al. proposed a rapid method for the evaluation of ship collision damages in real operations [52]. This method identifies critical collision scenarios during actual operations and then evaluates damage extents. Significantly, it is the first original study to calculate the possible consequences (the penetration and damage lengths) of collisions assuming that the ships do not undertake evasive actions, as seen in Fig. 14. The method can demonstrate the potential consequences if the crew makes incorrect collision avoidance actions or fails to take any action. This constitutes an important achievement in the development of intelligent decision support systems.

(3) Machine learning methods

Even though the SEM is fast in terms of calculating damage extends following collision and grounding events, it is difficult to design complex scenarios, considering different ship types, specifications, dynamics, etc. As an alternative, Machine learning (ML) methods may be utilised for the evaluation of structural response [210,211]. Examples are the Support Vector Machine (SVM), the K Nearest Neighbours algorithm (K-NN), Artificial neural networks (ANN), and ML can learn complex nonlinear structural systems in real operational conditions. For example, Braidotti et al. proposed an ML model that may be used to predict the damage consequences using SVM. The authors indicated that the proposed model could capture the flooding mechanism due to ship damage [212]. Silionis et al. designed an ANN model to predict ship damage under extreme actions. The proposed model was trained by using the data from FEM. The results indicated that the trained model could be used to predict ship damage rapidly [213]. Furthermore, to enhance flooding risk assessment through real-time damage evaluation, a damage surrogate model was proposed. This model aims to capture the nonlinear relationship between accident scenarios and damage extents using ML methods. It was trained using 4400 damage instances, and the training data was generated through the direct crash method using the super-element code SHARP [214]. These rapid and real-time methods represent a significant achievement in the development of intelligent decision support systems in the future.

(4) Applications on the evaluation of collision and grounding damages

Coupled methods can be used for the evaluation of ship collisions [215–217] and groundings [181,218–220]. The details of the state-of-the-art ship collision assessment methods (from internal and external mechanics perspective) can be found in these review papers

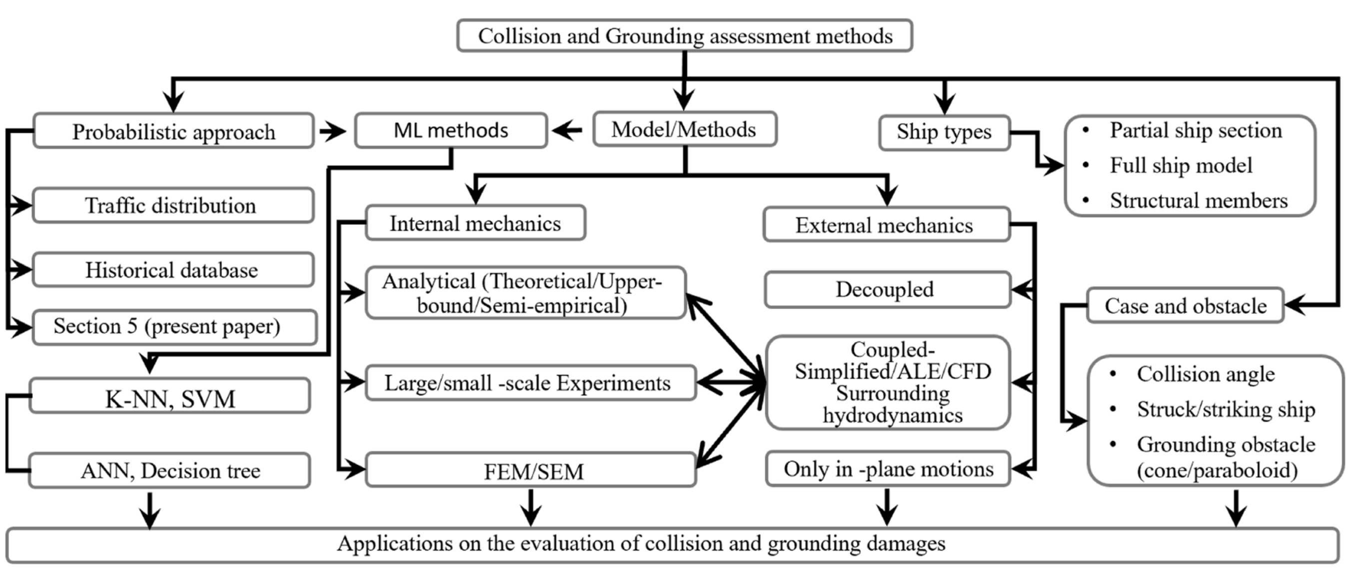


Fig. 13. Ship collision and grounding assessment procedure.

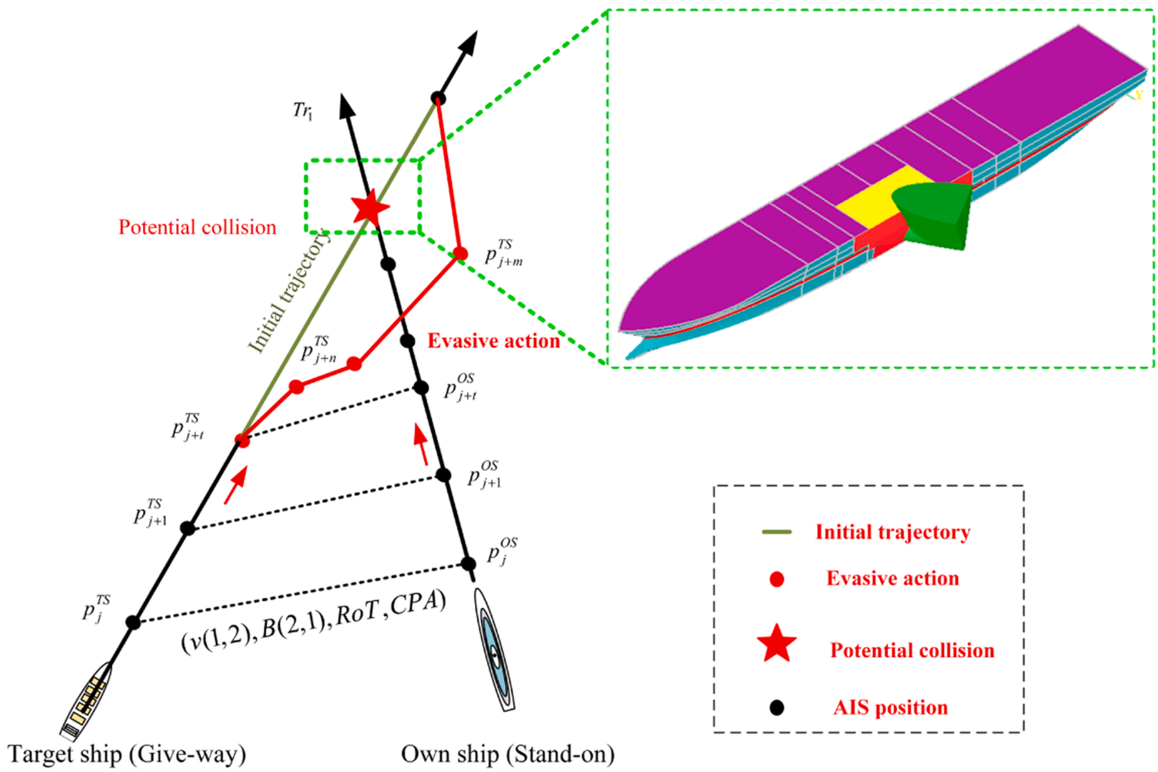
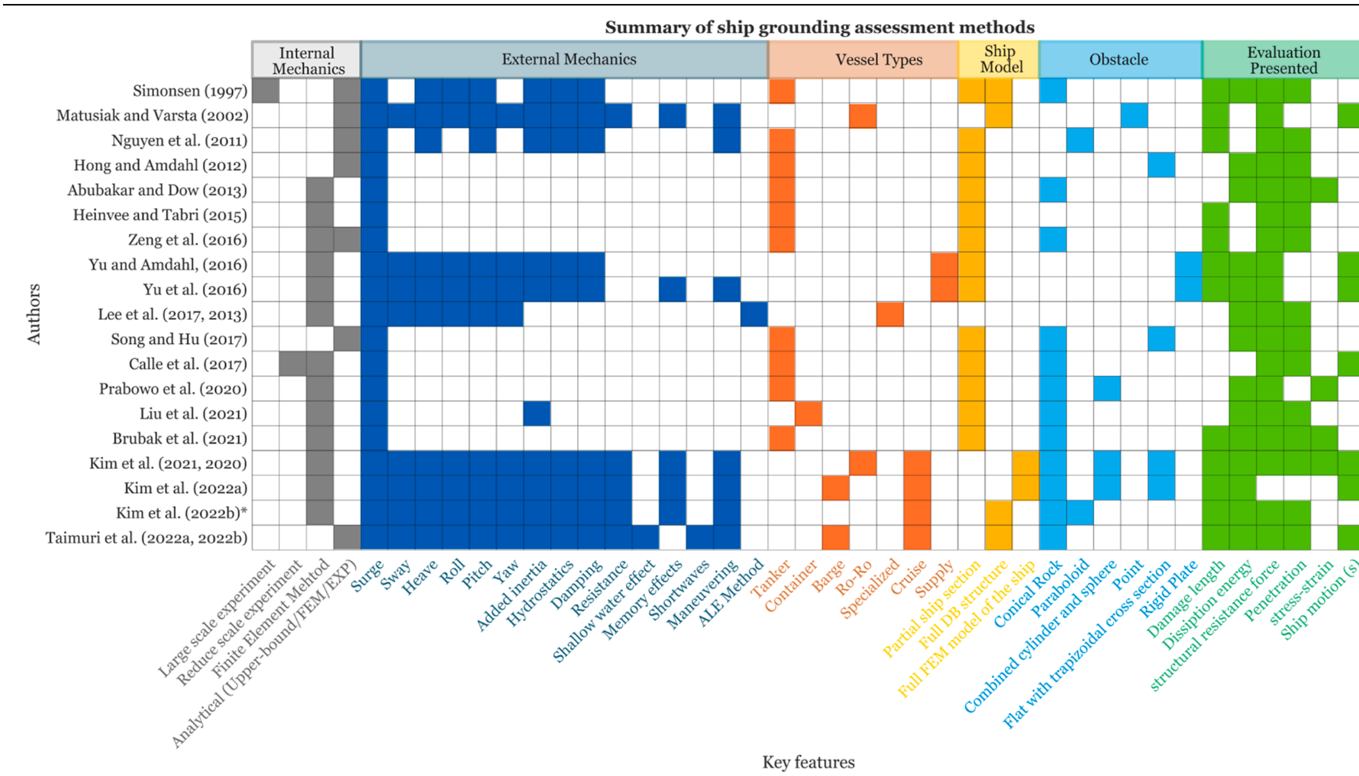


Fig. 14. The analysis of possible collision damages in real operation [52].

[21,27,206,221]. The state-of-the-art lacks recent models of ship grounding assessment. Table 2 summarizes the advantages and disadvantages of ship hard grounding assessment models published over the previous quarter-century. The evaluation is based on internal and external mechanics, explored ship types, structural model features, rock shapes, and evaluations presented in relevant papers. It demonstrates

Table 2
Ship hard grounding assessment methods.



how little emphasis has been placed on rapid multiphysics models idealizing coupled ship grounding dynamics [53,54], see Fig. 15.

The summary presented in Table 2 concludes that, to date, only a few studies have investigated the effects of direct multi-physics-based coupling in the assessment of grounding dynamics [222–224]. For instance, Abubakar and Dow employed the Finite Element Method (FEM) to conduct numerical indentation tests, revealing that flexible structures (lacking stiffeners) exhibit superior crashworthiness compared to rigid structures (equipped with plate and girder stiffeners) [225]. On the other hand, Heinvee and Tabri leveraged FE analysis to deduce an analytical equation for grounding forces, considering variables such as rock penetration depth, rock shape, ship length, and the height of a ship double bottom [226].

To propose an alternative to Simonsen's method [222], Zeng et al. proposed an alternative approach for plate tearing over a conical rock. The authors, instead of considering a cone generator line, they focused on the contact area between the conical rock and the plate, thus formulating an analytical expression for plate resistance forces [227]. Yu and Amdahl introduced a coupled approach that integrates 6-DoF hydrodynamics to simulate a soft grounding scenario involving a supply ship colliding with rigid plates [228]. This work extends their earlier research [228] by incorporating a potential flow solver to calculate the ship hydrodynamics during grounding over a rigid plate [229]. The evaluation of crashworthiness in bottom grounding employs finite element analysis (FEA). The numerical approximation is validated by direct comparison against laboratory experiments using an indenter plate and yielded to favorable outcome [230]. A benchmark study addressing key aspects of FEA pertinent to ship grounding is presented in [231]. More recently, the developed models demonstrate that strongly coupled ship grounding dynamics can be idealized by advanced solvers such as Arbitrary Lagrangian-Eulerian (ALE), and coupled nonlinear FEM with potential flow hydrodynamics (Green function-based) solvers [181,232–234].

Computing costs associated with high-fidelity multi-physics methods imply the need to develop reduced-order methods for use in rapid assessment, and operational monitoring. For example, Kim et al. recently presented an alternate technique that combines simplified spring elements for the idealization of the hydrodynamic restoring forces [218]. Their approach couples hydrodynamics with FEA to evaluate structural deformations during grounding. Whereas results are reasonable, it is well demonstrated that uncertainties associated with the implementation of external mechanics models (e.g., restoring stiffness and damping in the spring model) may influence the simplified models. The computational economy of the FEA models remains critical. Another solution could be offered by coupling the super-element method with rigid body dynamics [216]. The method idealizes Fluid-Structure Interaction (FSI) effects in the way of contact. In the super-element method, the ship structure is divided into several macro-elements (e.g., plates, intersection, transverse, and longitudinal members) the mechanics of which are described by closed-form analytical formulations accounting for the structural resistance force. These elements deform individually, and the contribution is added to give a total energy of deformation [235]. The study confirms the validity of the super-element method and demonstrates a significant reduction in computational time [219]. Using a non-linear FEA-coupled FSI model contributes to more realistic idealizations. However, the major constraints of using FEM and FSI models are cost and time. Both these constraints make crashworthiness and probabilistic damage stability assessment challenging to conduct.

A significant drawback within these methods lies in their oversimplification of the influence of evasive actions (e.g., vessel maneuvering capabilities [49]), the representation of ship geometry and scantlings beyond as-built conditions, and the accuracy of material conditioning and hull strength profiles [179,180]. They tend to underestimate the intricacies of complex accident scenarios, encompassing collision and grounding angles, as well as collision and grounding points on a ship [181].

Collisions and groundings stand as pivotal maritime incidents and may lead to the loss of ship damage stability [236]. In this area of work, probabilistic methods may help portray damage characteristics through the establishment of statistical distributions [237,238]. Direct methods engage in the depiction of damage characteristics through scenario-based simulations [51,52]. Both methods can be used to evaluate risk control options [236] via the use of active measures [239,240]. Examples are ship reinforcements designed to curtail potential breach dimensions [241]. Passive solutions aim to fortify vessel residual stability by counter-ballasting, foam application, and the utilization of CO2-based fire systems to activate airbags within compromised compartments [242]. Other solutions may involve augmenting the number of watertight doors [243] or reconfiguring the ship's internal layout [244]. Currently, the so-called "Adaptive Reconfigurable Safety Technology - AREST" represents a holistic approach that encompasses both passive and active solutions, offering a versatile framework for mitigating the risks associated with collisions and groundings in the maritime domain [236].

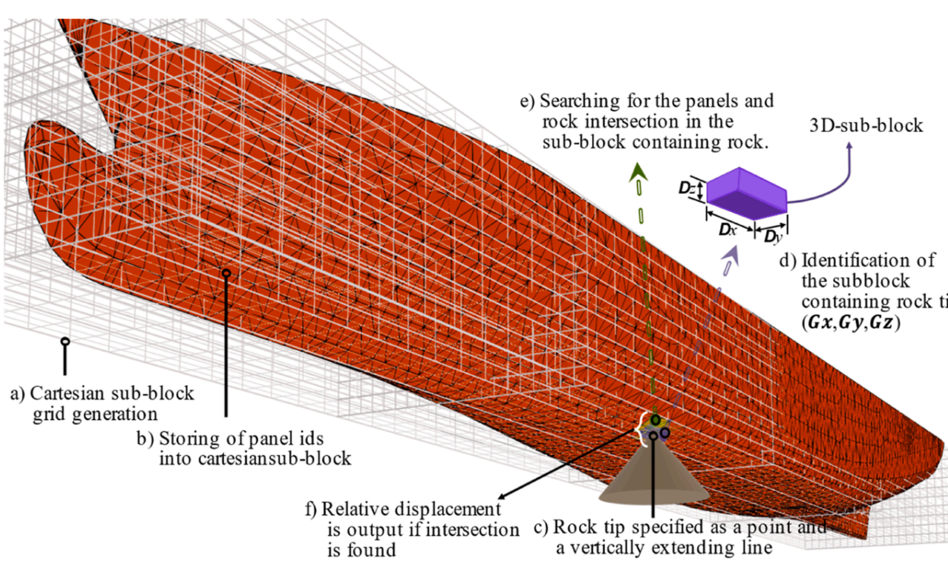


Fig. 15. The process of grounding damage evaluation [53].

6. Ship motion prediction for proactive prevention

Seakeeping prediction methods may be used to better understand the dynamic behavior of ships in stochastic seaways. Hence, seakeeping models are useful during maritime operations, such as navigation models, loading during offshore operations (e.g., replenishment at sea models), ship design, and safety assessment. "Advanced Autonomous Waterborne Applications" by Rolls-Royce (2016) highlighted the crucial importance of taking into account a ship's independent maneuvers in shallow waters, as well as its motion characteristics (including wave-excited motions such as heave, pitch, and roll) when addressing collision and grounding avoidance [235,245,246]. The prediction of ship motions and sea loads in real conditions offers a distinctive opportunity to establish proactive preventive measures [71,247,248], which is another key component of the intelligent decision support system, as illustrated in Fig. 3.

6.1. Mathematical methods

A ship operating at sea moves as a rigid body at six degrees of freedom and should be able to sustain the combined actions from wind, waves, bathymetry (shallow water or deep water) and ocean currents. Derivation of mathematical models that can help us idealize the combined effects of such environmental conditions on ship responses, especially under accidental scenarios (e.g., collision and grounding), is scarce and can be challenging in terms of maritime safety risk management. This is because of the mathematical rigor, modelling assumptions and uncertainties associated with existing models as well as their computational constraint economy that limits practical use. Traditionally, principles of Newtonian and wave mechanics are used to derive the equations of motion of ships as rigid bodies. Manoeuvring theory is implemented to model external forces and moments acting on a ship [249].

Generally, the mathematical model of the Manoeuvring Modelling Group (MMG) standard method served as the foundation for the majority of simulations [250]. However, most studies into collisions and groundings do not take into account the combined impact of ship manoeuvring before risk mitigation. Most algorithms rely on ship kinematics and do not take into consideration ship dynamics or the external forces acting on ships along an evasive path [251,252]. Correct estimates of ship manoeuvring characteristics in the time domain are necessary to improve decision-making ability. For example, Ståhlberg et al. emphasized the relevance of ship velocity and time history in calculating evasive manoeuvres in the event of a collision [253]. Yet, very few studies account for the influence of ship maneuvering under the action of the surrounding environment [45,254,255]. Ship maneuvering under the influence of the surrounding environment introduces a complex and dynamic interplay of factors that can significantly affect the outcomes of collision and grounding incidents [54,149,151]. This interaction involves the combined effects of hydro - meteorological conditions, the influence of bathymetry (shallow/ deep waters) and other environmental variables on ship dynamics. Incorporating these environmental factors requires good understanding of how hydrodynamic actions may influence ship dynamics (e.g., maneuvering capabilities) and how these interactions can influence collision/grounding risks and maritime safety. While some studies may focus on specific aspects of ship motions or environmental conditions [49], the full integration of ship maneuvering within the context of the surrounding environment is a challenging task that demands the development of sophisticated modelling and simulation methods that are well-validated by experiments [256]. To date, only a limited number of research endeavors ventured into exploring this complex relationship.

6.2. Emerging technologies

Classic model testing is the most accurate method for gathering information on wave-induced ship motions for use in ship design. However, its applicability to safety operations is challenging. Emerging approaches may be used to address this issue as computational power grows. In addition, research in machine learning science may help overcome problems associated with identifying coefficients and hydrodynamic derivatives in real-time via the utilization of model tests or open sea-trial data.

(1) Ship manoeuvring system identification using ML

With the continuous development of sensor technology and identification technology, ship manoeuvring system identification methods emerged as a unique set of methods for ship motion prediction. Ship manoeuvring system identification methods are governed by parametric and non–parametric estimation models.

Parametric estimation methods are employed for the quantification of ship dynamics, given that available ship mathematical models (see more in Section 6.1) are in place to train big data streams. For example, to identify the hydrodynamic derivatives of a mathematical model, namely, the 3-DOF Abkowtiz model, the nu-SVM is used [257]. To determine the hydrodynamic derivatives of an MMG model, the extended Kalman Filter (EKF) method is adopted [258]. Recently, it has been observed that these methods can handle ship motion features with the aim of determining hydrodynamic derivatives. These identified ship models have been used to determine multi-ship collision avoidance options for intelligent ships and traditional ships [70,74]. Notably, Taimuri et al. proposed a predictive analytics method to determine grounding avoidance based on a rapid 6-DoF ship manoeuvring model in real operational conditions [53].

Non-parametric estimation methods are used for the quantification of ship dynamics by training big data streams [259]. Non-parametric estimation models use ML methods or algorithms to identify ship motion features. The common models are: Artificial Neural Networks (ANN) [260], Gaussian process regression [261,262], Long Short-Term Memory (LSTM), locally weighted learning methods [263], as well as the transformer [264]. These methods were adopted to learn the ship motion features by using simulated free-running tests or open sea-trial data. Recently, Lou et al. proposed a novel ANN model for accurately predicting the 3-degrees-of-freedom motion of unmanned surface vehicles under real operational conditions [265].

Most of the above-mentioned parametric or non-parametric models can be used to identify ship motion features and predict ship motions rapidly. However, they are trained by the data streams from available ship maneuvering models or a small sea–trial data sample. They may underestimate the influence of medium to long-term environmental conditions, shallow waters, and deep waters. To the best of our knowledge, the big data from real sea manoeuvrability tests are extremely difficult. Therefore, Zhang et al. proposed a transformer-based deep learning method to predict the ship motion dynamics [264]. The trained data were obtained from historical motion features from big data streams and a 6-DoF ship dynamics model. The results indicate that the model can capture the ship motion dynamics in real operations and the turning features of the ship, see Fig. 16. These trained deep-learning models are ready to use and can simulate ship motion under various hydrometeorological conditions. By iterating with the trained ship manoeuvring prediction model, ship manoeuvring commands can be tested. This allows for the determination and application of safe ship manoeuvring commands for collision and grounding avoidance.

(2) Ship trajectory prediction using ML

Idealisation of ship operational conditions is possible by suitable utilisation of AIS big data streams. Maritime transportation system pattern identification-based ship trajectory prediction methods successfully predict ship motion tracks in the spatio-temporal domain [266]. Such logic is useful for proactive maritime traffic management and accident prevention. Ship trajectory prediction methods can be classified into statistical methods [267–269], Machine learning methods [270–273], and deep learning methods [274–277]. Nevertheless, these studies are based on models trained to limited ship motion features using

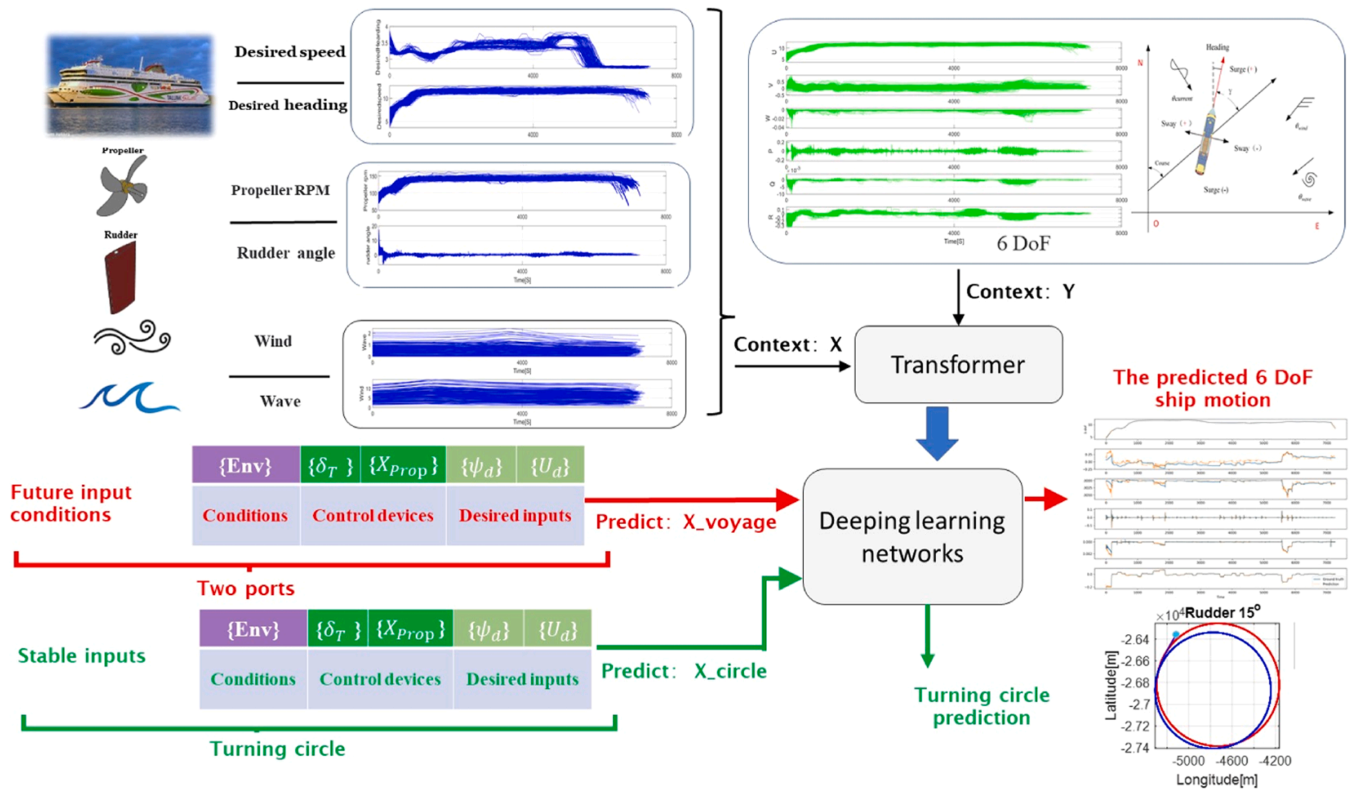


Fig. 16. Manoeuvring system and ship motion prediction in real conditions and in calm conditions [264].

only AIS data. They ignore operational conditions (waterway, environmental conations, etc.) and the ship system [278]. Thus, it may be difficult to capture the influence of sea loads on ship dynamics in real operations [279]. Recently, from the perspective of the maritime transportation system, Zhang et al. developed a Gaussian process regression method to predict time-varying ship motion trajectories, accounting for the environmental conditions [71]. Overall, as compared to the models of ship manoeuvring system identification, these studies underestimate ship control devices (rudder and thruster), resulting in ignoring some of the ship dynamic features (i.e., roll, pitch, yaw, etc.) in various seabed topologies. Additionally, the predictions made by these studies are typically short-term. These studies present challenges in testing and selecting safe ship manoeuvring commands, primarily because these methods do not adequately capture the ship manoeuvring system. Additionally, AIS data includes limited dynamic information about ship motions, thereby hindering the application of these studies in rigorous testing of ship manoeuvring for collision and grounding prevention [280,281].

Accurate mathematical methods and parameter identification approaches bring added value in accurate long-term manoeuvring/seakeeping predictions. However, it is worth noting that ship trajectory prediction methods are limited in terms of accounting for ship dynamics complexities [282]. Ship trajectory prediction methods exhibit constraints when it comes to effectively preventing collisions and groundings.

Grounding incidents occur when a ship unintentionally comes into contact with the seabed [49]. Shallow water effects, vessel manoeuvring characteristics and hydrodynamics are particularly crucial in this scenario [283–285]. Research shows that ship motion of relevance to groundings should delve into how hydrodynamic forces, including squat, trim, and interactions with the seabed [286]. On the other hand, ship collisions are dependent on hydrometeorological conditions (e.g., wind, wave, shallow waters), their influence on wave-induced motions (particularly heave, pitch and roll), ship – ship interactions, ship stability and traffic encounters.

7. Discussion

This section presents, results from accident statistical reviews. A discussion on the status of strategic research challenges and trends of relevance to intelligent decision support systems for collisions and groundings prevention is presented.

7.1. Limitations and challenges

An exploration of the technical prerequisites for establishing an intelligent decision support system aimed at collision and grounding prevention is undertaken (Fig. 1). This section not only highlights the essential criteria for such a system but also brings to the forefront the limitations and challenges that have bearing on collision and grounding assessment within the context of an intelligent decision support system. Moreover, these identified challenges offer significant directions for potential avenues of future research and development.

(1) Simplified collision and grounding avoidance process

The prevailing practice in many existing studies involves the oversimplification of the collision and grounding assessment process, as shown in Section 4. This oversimplification often leads to a lack of consideration for the intricate uncertainties associated with ship motions and potential accident consequences. Within these studies, actions taken to avoid collisions and groundings are conceptualized in an idealized manner, neglecting the complex interplay of the ship dynamic behaviour with its surrounding environment [287]. Notably, these analyses tend to overlook crucial scenarios where collisions and groundings are, in fact, inevitable. This oversight limits the precision and viability of the established models. In addressing this challenge, there is a compelling need to rigorously quantify the inherent characteristics of ship motion alongside potential damage scenarios. By incorporating these quantifications, the developed methods and models hold the promise of enhancing the capacity of involved ships to grasp hazardous situations with greater nuance in real conditions. A case study [53] exemplifies the potential of such an approach by emphasizing the significance of quantified ship motion features and probable damages as integral elements of a comprehensive collision and grounding assessment.

(2) Lack of grounding operational regulations

While operational risk and safety management regulations, like the COLREGs, play a pivotal role in shaping ship decision support to prevent collisions, a corresponding regulatory framework for grounding remains conspicuously absent (See more in Section 4.1). This existing regulatory disparity becomes particularly evident in operational practices where ship routing decisions are crafted based on static charts and empirical wisdom. In light of this, there emerges an urgency to conceptualize and institute a comprehensive set of operational risk and safety management regulations exclusively oriented towards grounding incidents. The establishment of such regulations should be supported by robust safety models and insights derived from ship science, thus laying the foundation for a sturdy framework that facilitates safe and well-informed decision-making in response to grounding risks. Moreover, a significant proportion of the prevailing grounding risk evaluation models disregard the dynamic nature of bathymetry maps. Furthermore, traditional navigation charts are inherently static, which could potentially result in an underestimation of water depths for ships operating in real-time conditions.

(3) Inadequacy of static risk analysis for dynamic maritime systems

While the significance of static risk analysis in the broader context of collision and grounding assessment cannot be understated, these approaches often grapple with limitations when confronted with dynamic maritime systems. The outcome of such analyses yields valuable insights for maritime authorities and policymakers, contributing to a proactive risk mitigation paradigm. However, the dominance of static methodologies frequently impedes the acknowledgement of dynamic risk scenarios, thereby rendering them ill-equipped to furnish comprehensive prevention strategies for ship navigating within real environmental conditions. A judicious resolution to this challenge necessitates an innovative amalgamation of static and dynamic risk analysis techniques. This synthesis could potentially culminate in the creation of multifaceted tools designed to proactively prevent maritime accidents, with potential applicability in specific regions or designated waterways.

(4) Underestimation of operational conditions

The discernment that the effects of collision and grounding scenarios significantly vary contingent on distinct operational conditions is widely acknowledged in scholarly discourse [47,48]. Nevertheless, a holistic comprehension of the intricate characteristics that characterize waterways, environmental contexts, traffic dynamics, and the uncertainties underpinning ship motion is an intricate endeavor. The introduction of big data analytics alongside a judicious integration of multi-source data repositories offers a promising pathway to recovering and interpreting historical events. This confluence has the potential to illuminate new facets of grounding and collision assessments, thereby fostering a more informed and holistic perspective.

(5) Need for improved ship motion prediction tools based on large-scale datasets

Accurate prediction of ship motions is essential within modern automatic control systems and decision support frameworks, where precision impacts operational safety and efficiency. Despite advancements, existing models often overlook the intricate interplay between ship maneuvering and environmental conditions, leading to significant discrepancies between predicted and actual ship motions, especially in challenging hydrometeorological conditions.

To overcome these limitations, the adoption of ML methodologies is crucial. ML provides a robust framework for integrating and analyzing extensive datasets, including high-resolution spatial and temporal environmental data, ship performance metrics, and historical navigation records. This integration allows ML models to accurately discern and predict the complex dynamics of ship motions more effectively than traditional models.

Moreover, the use of ML in ship motion prediction tools facilitates the continuous refinement of models through adaptive learning. This feature enables real-time adjustments based on new data and changing environmental conditions, thereby enhancing predictive accuracy under actual operational conditions. For example, ML algorithms can dynamically adjust predictions in response to real-time weather updates and sea state conditions, crucial for safe navigation in adverse weather.

However, the success of ML-driven tools for predicting ship motions hinges significantly on the availability and quality of big data. Fig. 17 illustrates the amount of data required to train the ML model and the learning capacities of the selected deep learning model [288]. To support the development and training of more sophisticated ML models, the establishment of comprehensive and accessible data repositories is essential. These repositories, supported by industry-wide collaborations, not only aid in model development but also enhance the reproducibility and scalability of research findings. By promoting data sharing and standardization, the maritime industry can accelerate the advancement of predictive models that are robust and adaptable to various maritime challenges. The future of ship motion prediction is likely to depend heavily on the integration of ML techniques with large-scale, diverse datasets. This approach will enable a more nuanced understanding and anticipation of ship motions in real operational conditions, leading to the development of more reliable and effective navigation and control systems.

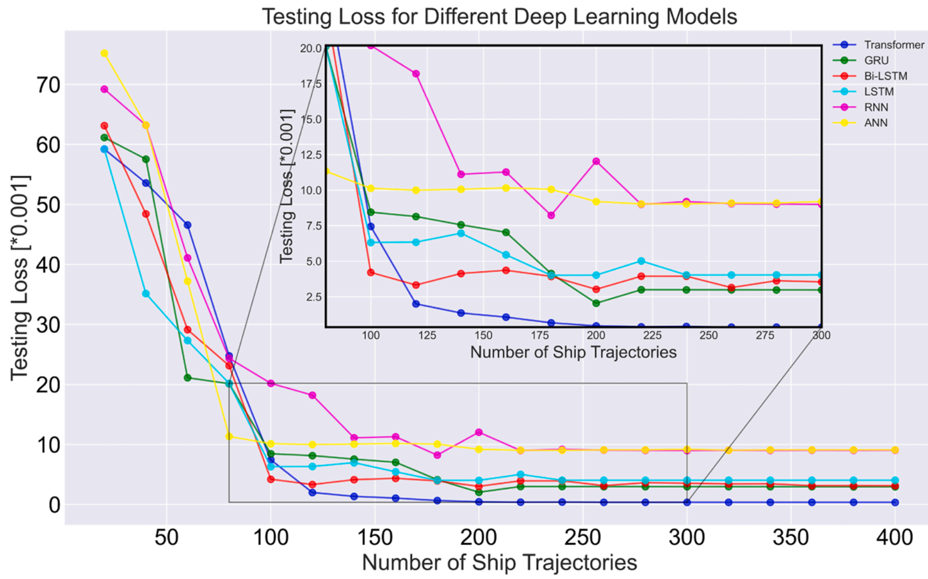
(6) Need for improved rapid damage prediction methods

The current landscape of damage evaluation techniques draws from a diverse array of methodologies encompassing the FEM, empirical analyses, experimentation, and analytical approaches. Notably, these approaches tend to abstract ship manoeuvrability to a simplified and often unwieldy extent. Subsequent to their abstraction, these approaches necessitate the implementation of mathematical sub-models to compute displacement and deformation—a process that is computationally intensive and rigid. Unsurprisingly, these limitations hinder their practicality and applicability to ships navigating within time-varying environmental conditions. Furthermore, an analysis of the ultimate limit state of ships subject to biaxial bending in both intact and collision/grounding-damaged conditions involves assessing the structural integrity of the ship to ensure it can withstand extreme loading conditions. Such a study should be further explored [289]. The exploration of emerging techniques, particularly those grounded in ML, presents a promising avenue for the prediction of maritime accident consequence [290]. Such ML-driven models, when effectively trained using copious simulation and experimental data, demonstrate the capacity to accurately apprehend the intricacies of crushing mechanisms and expeditiously predict structural damages [22,210]. Yet, it imperative to acknowledge that the accomplishment of this potential necessitates the collation of substantial datasets alongside meticulous training, a formidable yet rewarding undertaking.

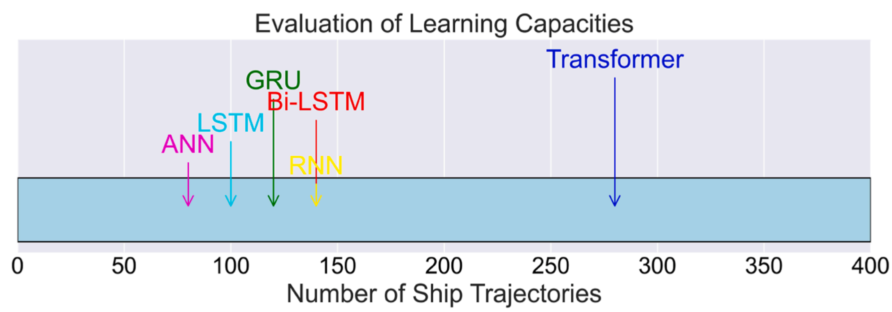
(7) Disproportionate emphasis on collision and grounding prevention studies

The landscape of research concerning the prevention of ship collisions and groundings presents a notable imbalance. Despite a substantial 1548 journal papers being published in the last two decades, the distribution of studies across these two domains is far from equitable, as illustrated in Fig. 18. Specifically, the volume of research dedicated to collision prevention surpasses that of grounding by a factor of 4.52. This disparity is noteworthy considering that more than 15 % of maritime accidents are attributed to groundings. A conceivable explanation for this asymmetry could stem from a limited comprehension of the intricate bathymetric conditions coupled with a constrained understanding of the dynamic interactions characterizing grounding incidents.

To address this issue, it is advisable to adopt a comprehensive research perspective that accounts for both collision and grounding



(a) The influences of different lengths of training data on testing loss evaluation.



(b) The learning capacities of the selected deep learning model.

Fig. 17. The evaluation of data required to train ML models for predicting ship motions [288].

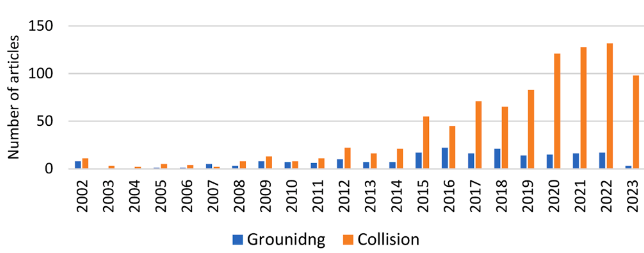


Fig. 18. The research distribution on collision and grounding between 2002 and 2023.

scenarios. Rather than solely concentrating efforts on collision prevention, a more balanced approach that encompasses grounding prevention is warranted. Such a recalibrated approach holds immense potential to significantly bolster safety across the spectrum of ship design and maritime operations. By fostering the development of maritime accident prevention tools and decision support systems with a dual focus on both collision and grounding, the maritime industry can expect to reap substantial safety benefits. This strategic shift in research direction not only aligns with the realities of accident occurrences but also positions the field to proactively enhance safety measures within the broader maritime context.

7.2. The intelligent decision support system for assisted manoeuvring

The goal of intelligent decision support systems for ships is to transform 'Unknowns'—typically human errors—into 'Knowns' for onboard crews through navigation risk analysis, consequence evaluation and motion predictions [35,291,292]. This is particularly important for assisted manoeuvring, enabling crews to anticipate and effectively manage potential challenges in advance for safe navigation in real operational conditions. The following sections introduce the assisted manoeuvring system and its technical requirements.

7.2.1. Assisted manoeuvring

An assisted maneuvering system is equipped with advanced perception and planning capabilities, enabling ships to enhance safety, navigation, maneuvering, and control functions while providing decision support for crews. This system is designed to timely detect navigation risks, rapidly evaluate potential consequences, and offer predictive motion capabilities based on control commands.

The primary objective of assisted maneuvering is to provide the crew with reliable and secure decision support. Essential features of these systems include recommendations for speed (propeller RPM) and course (rudder angle), motion state prediction, and guidance for safe ship motion trajectories. Assisted maneuvering systems facilitate real-time virtual simulation and rapid evaluation, delivering these critical recommendations to reduce human errors.

More specifically, the assisted maneuvering system enables the testing of ship maneuvering commands based on virtual simulations by integrating navigation risk analysis, consequence evaluation, and motion predictions. This enhances safety and operational efficiency, actively involves crew members, and provides crucial decision support for navigation. Additionally, the system offers recommendations on course and speed, predicts motion states, and supports data analysis and system optimization.

7.2.2. The technical requirements of the assisted manoeuvring systems

The introduction of the assisted manoeuvring systems requires the practical implementation of Eq. (1) intending to reduce the probability and potential impact of collisions and groundings. Manoeuvring commands should be designed with the objective to minimise (1) the probability of incidents to the greatest extent possible; and (2) the consequences of incidents if the probability cannot be entirely eliminated. Key technical requirements in such a system can be summarized as follows:

(1) Prediction of uncertain ship motions in time-varying environmental conditions

The dynamics of ship motions in the presence of hydrometeorological conditions introduce inherent uncertainty. Notwithstanding this, the accurate quantification of ship dynamics in real operational scenarios remains a challenge for the crew on board and may often result in the oversight of dangerous situations [287]. The human based decision-making system is predominantly passive. This is because it mainly relies on projected ship manoeuvring commands to estimate short-term ship motion trajectories [293]. Furthermore, testing these ship manoeuvring commands to select the safest option proves to be challenging [294].

Existing ship motion prediction methodologies (see Section 6), whether they are based on mathematical models, fall short in terms of seakeeping prediction accuracy. This deficiency arises because mathematical approaches rooted in physics, struggle to faithfully depict the intricate interactions between wind, waves, currents, and ship motion in stochastic conditions. Modern simulation methods (e.g., computational fluid dynamics methods or potential flow time domain methods) suffer from computational economy and complexity deficiencies. The accuracy of parametric models lags behind from the perspective of suitably utilising big data analytics. On the other hand, the application of non-parametric methods for ship manoeuvring system identification demands an ample amount of maritime environmental data as reference samples. This is because environmental factors like wind, waves, and currents exhibit highly dynamic spatiotemporal variations. The currently employed shipborne sensing equipment confronts difficulties in precisely capturing real-time changes in wind, waves, and currents within navigational waters [295]. As a result, the realization of big data-driven ship motion predictions, considering the ever-changing influences of wind, waves, and currents, becomes increasingly essential (see Fig. 19). As illustrated in Fig. 19, information perception can be achieved through the integration of multiple data sources. Additionally, the ship manoeuvring system identification method can be utilized to the nonlinear relationship between the ship manoeuvring commands (propeller rpm, and rudder) and ship dynamics reflecting hydrometeorological conditions and then predict ship motion trajectories in real operational conditions, as detailed in the study [264].

(2) Proactive cognition of collision and grounding risks for ongoing ships

As discussed in Section 4, static methods underestimate time-varying ship motions and operational conditions. To address this limitation, a dynamic risk analysis methods are required to quantify the probability of collision and grounding from a spatial-temporal perspective. However, a universally accepted risk threshold is not available [47,48].

To fill the gap, the evaluation of navigation risk for an operational ship entails the comprehensive assessment of both collision and grounding risks, as denoted in Eq. (1). This assessment integrates considerations by probability and potential consequences. Optimizing the probabilities of collision and grounding offers the potential for achieving enhanced cost-effectiveness. However, in cases where the avoidance of collisions and groundings proves unfeasible (i.e., when complete elimination of probability is not possible), the focus should be on the minimization of potential consequences. Thus, the development of proactive cognitive tools for real-time assessment of collision and grounding should be given priority (Fig. 20).

The difficulties of existing methods relate to oversimplification in ship dynamic assumptions (e.g., vessel manoeuvring capabilities), the inadequate representation of ship geometry and scantlings, the insufficient consideration of materials and profiles, and complex accident scenarios. The timely and accurate damage assessment is another key challenge that hinders the implementation of modern methods in decision support systems. A meaningful alternative may be the development of a ship accident consequence simulation database, including massive possible ship collision and grounding scenarios and corresponding damages [52,210,214]. The database can be utilized to train a real-time damage evaluation method. When combined with a ship motion prediction model, it can be employed to assess the risk of collision and grounding in advance for proactive cognition.

(3) Rapid iteration testing of ship manoeuvring commands

Existing collision and grounding assessment methods underestimate the intricate interplay between ship dynamics, systems, and navigation patterns. Leveraging the benefits of a precise ship motion prediction

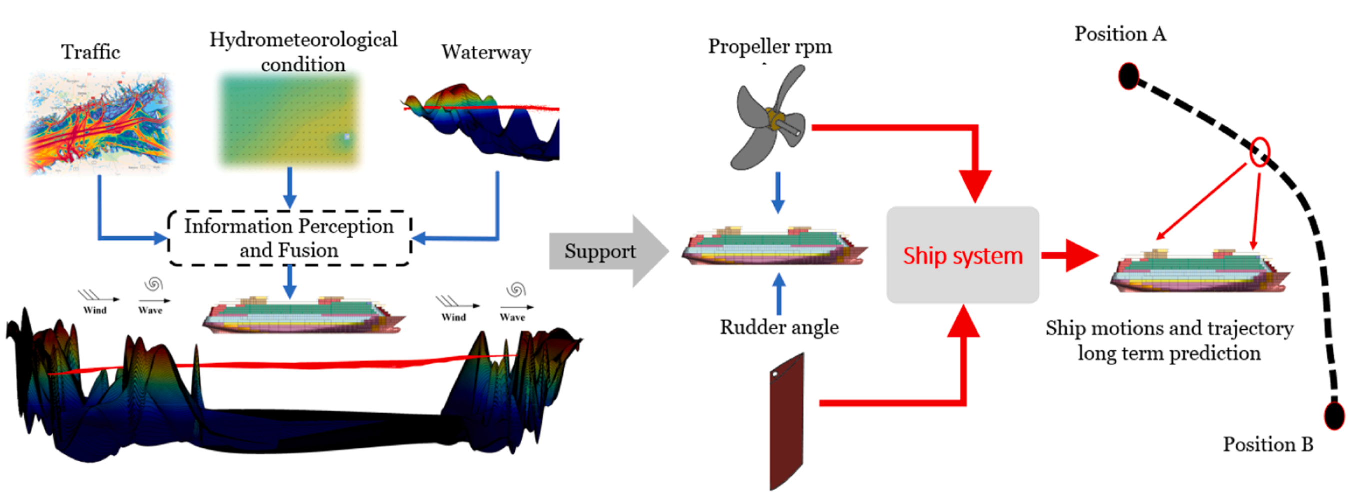


Fig. 19. Information perception and ship manoeuvring system identification for the prediction of ship motions in real operational conditions.

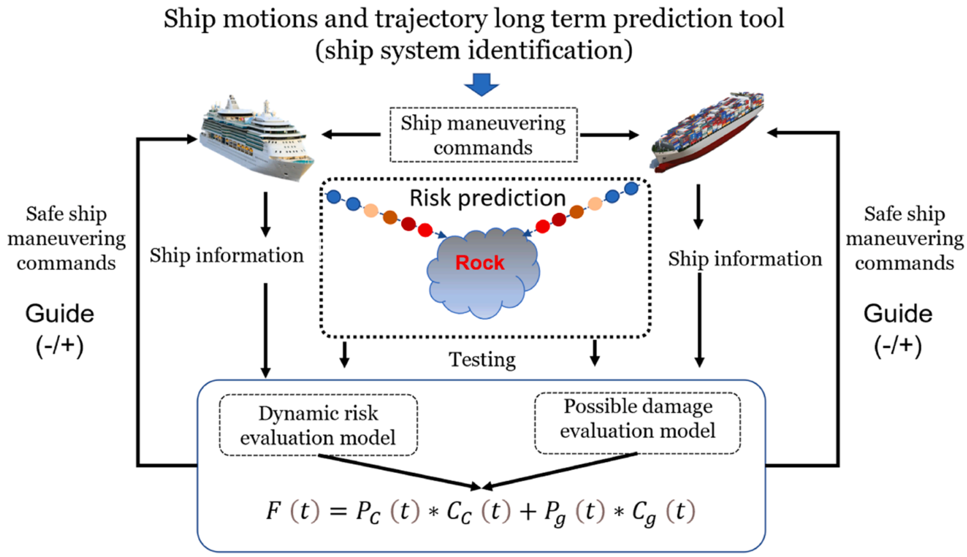


Fig. 20. Proactive cognition method of collision and grounding risks for ongoing ships based on ship motion predictions.

model (Fig. 19) and a dependable proactive risk cognition model (Fig. 20) may lead to significant improvements in terms of ship safety.

Testing methods are designed to evaluate collision and grounding avoidance actions and provide reliable ship manoeuvring commands. Fig. 21 illustrates the iterative testing process used to determine safe ship manoeuvring commands. In scenarios where collision and grounding are potential risks, a testing method that combines a ship motion prediction model with a proactive risk cognition model is employed. This approach tests all possible avoidance actions (ship manoeuvring command settings), enabling the identification and application of safe ship manoeuvring commands to prevent collisions and groundings. For instance, a ship manoeuvring command is labeled "dangerous" in a state of adverse consequences (Ships operating along dangerous trajectories lead to collisions and groundings), whereas it is deemed "safe" in the absence of undesired outcomes (collisions and groundings avoidance). These tested safe ship manoeuvring commands can be provided to crews for determination. Therefore, such a testing method can support decision support by identifying and selecting safe ship manoeuvring commands to prevent collisions and groundings.

7.3. The trends in technology development for collision and grounding prevention

The shipping industry has conventionally placed a significant reliance on expert judgment [296]. However, the findings discussed in this paper showcase an escalating inclination toward incorporating digitalization in relation to actual operational scenarios [295]. The growing influx of data and the emergence of new technologies can be harnessed

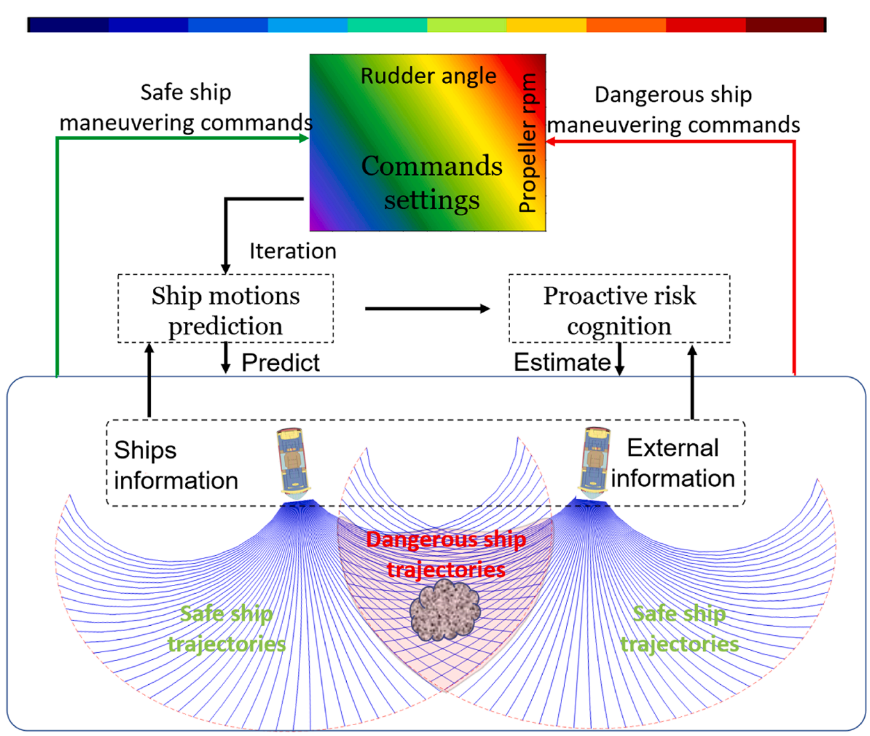


Fig. 21. Iteration testing for the determination of safe ship manoeuvring commands.

to gain deeper insights into the impact of traffic patterns, ship dynamics, environmental conditions, and waterway specifics on ship collisions and groundings. Rapid predictive methods, including the utilization of big data and AI, are fundamental within this evolving landscape of digitalization.

7.4. Digitalization in maritime

The Internet of Things (IoT) constitutes a worldwide interconnection of tangible and virtual entities, facilitating communication and management of big data of ships [297]. Cloud Computing offers storage and easy access to data. Big data analytics reinforces real-time decision support processes [295]. Intelligent Simulation enables the virtual testing of systems. Augmented Reality has the potential to assist crews with navigation under adverse conditions [298].

The integration of multifaceted information into decision support systems holds the potential to significantly enhance active ship safety management (Fig. 22). This capability arises from their capacity to facilitate the pre-processing and storage of diverse data sets within high-performance repositories. Examples of such data encompass AIS traffic and waterway data, hydro-meteorological information, and bathymetry data. The inflow of real-time data (ranging from the seabed and hydrometeorological data to waterway and traffic data) can be seamlessly received, stored, and analyzed by advanced real-time decision support tools.

These tools can effectively identify intricate ship traffic patterns and pinpoint high-risk areas, thus ensuring adherence to regulations and navigation standards. Furthermore, they could capture ship motion patterns and prognose ship dynamics in real conditions. However, the maturity of a risk framework grounded in such comprehensive knowledge of ship theory and emerging technologies remains embryonic.

7.5. End-to-end (E2E) learning methods for the development of rapid predictive models

A better understanding of predictive analytics is essential for the proactive accident prevention of ship collisions and groundings [53, 299]. The review presented in this paper suggests that most simulation methods are computationally costly and therefore hard to implement. Rapid predictive methods accounting for hydro-meteorological conditions and ship motion trajectories could better assist with the evaluation of consequences and hence the development of proactive risk cognition models.

AI methods can rapidly capture and predict ship motions and crushing dynamics. End-To-End (E2E) learning involves training a complex system, typically represented by a single model such as a Deep Neural Network. This model encapsulates the entire target system, bypassing the intermediate layers that are commonly found in traditional pipeline designs. However, even these models in their current format are decoupled in the sense that they realize dynamic risk analysis ship motions and the effects of possible damages independently [52, 264]. A first attempt to integrate these methods into the E2E model is depicted in Fig. 23. The overall workflow of the E2E model involves data collections, predictive detection, and evaluation in the first stage, followed by training, testing and recommendation in the second stage.

The method consists of the two stages identified below:

(1) Stage I: Using digitalization techniques to train a rapid predictive model

Digitalization techniques onboard ships can gather extensive streams of big data, encompassing data related to ship manoeuvring, corresponding ship dynamics, operational conditions, ship traffic in the vicinity of a ship, etc. These data are then utilized to construct a data-driven ship manoeuvring system identification model for the prediction of ship motions. The latter, functions analogously to a digital twin and accounts for ship dynamics. Big data streams and ship motion prediction also serve the purpose of detecting critical scenarios of relevance to collisions and groundings in advance. In turn, each critical scenario and the corresponding ship maneuvering commands allow for the assessment of damage extends in advance, accounting for ship dynamics in real conditions [52,54] (Fig. 23).

Advanced simulation tools (or computational experiments) might be deployed to generate training data that considers both ship maneuvering commands, ship dynamics and crashworthiness effects. These systems should include databases for ship maneuvering coefficients, propulsion data (propeller and rudder settings), and environmental conditions as inputs as shown in Fig. 23. All possible ship maneuvering commands are then evaluated and classified into outcomes, which are documented as safe maneuvering, dangerous maneuvering, and accidental maneuvering.

Using this comprehensive dataset, the generative pre-trained model is trained to integrate information from both ship maneuvering commands, ship dynamics, and crashworthiness simulations. This allows the

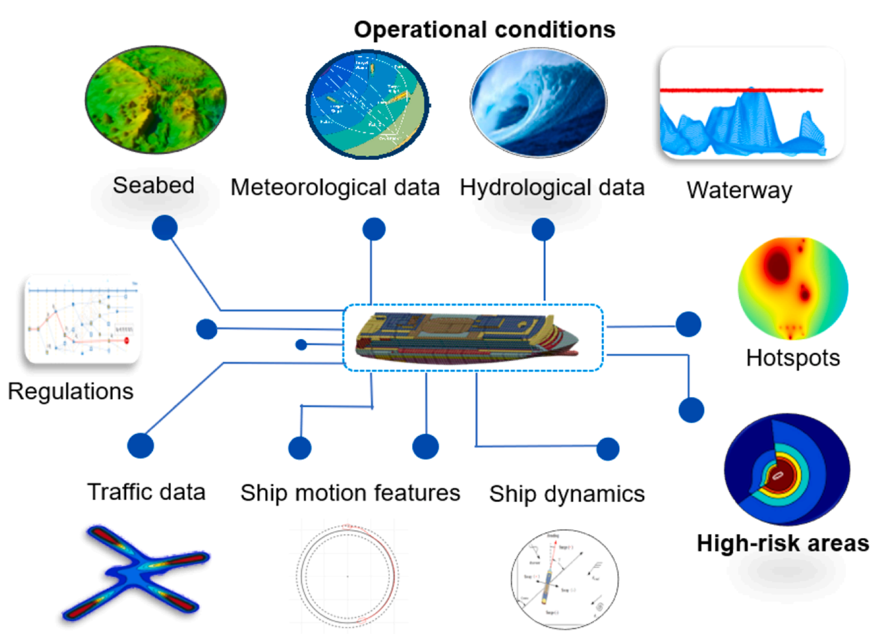


Fig. 22. The information fusion for the development of the intelligent decision support system.

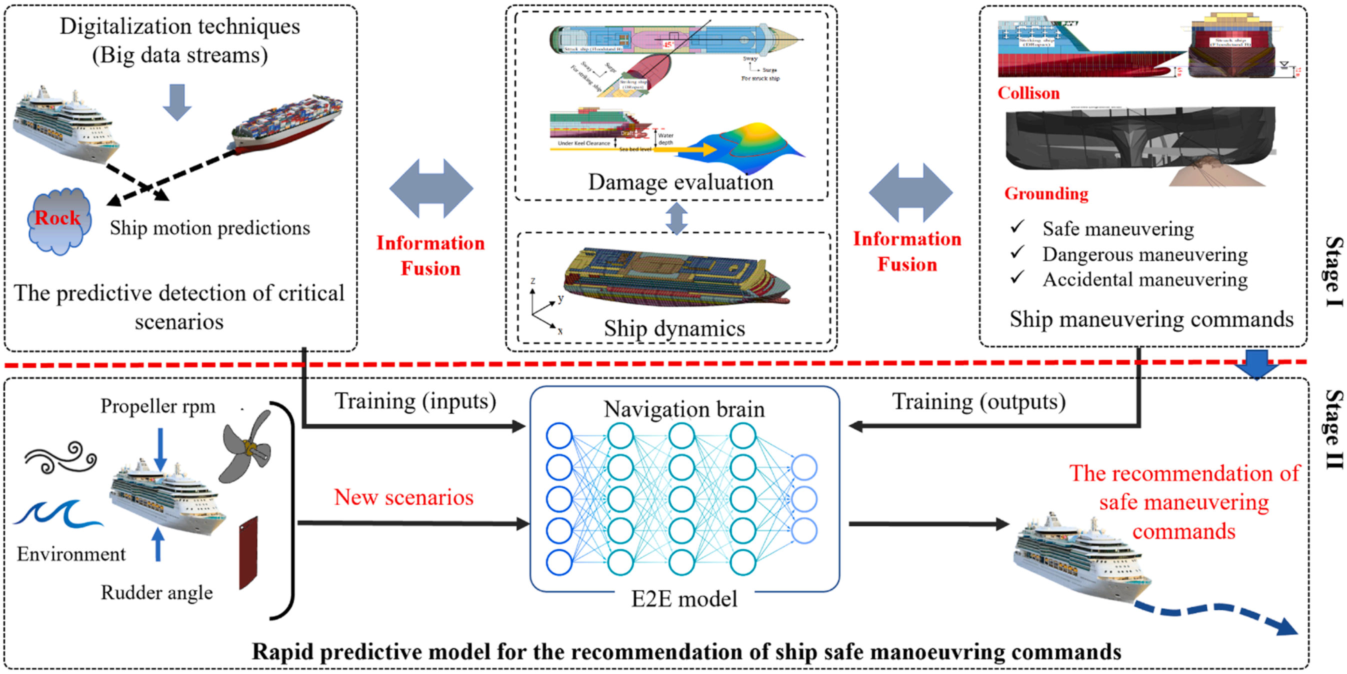


Fig. 23. A flowchart of rapid predictive method (E2E model) in the intelligent decision support system.

model to accurately evaluate the outcomes of different maneuvering commands by capturing the intricacies of ship responses to various conditions. This dual-source approach ensures a robust understanding of critical scenarios and ship avoidance behaviors [214,264].

(2) Stage II: Intelligent decision support on safe ship manoeuvring commands

The trained model can be harnessed during the decision-making processes of collision and grounding avoidance. The proactive accident prevention loop is depicted in Fig. 23. The results should across all iterations within the loop consistently indicate ship manoeuvring instructions for collision or grounding avoidance will be issued. And then, the tested and selected safe ship manoeuvring commands can be provided to crews for decision-making for collision and grounding avoidance. By utilizing these advanced tools and data, the system can provide real-time recommendations for safe ship maneuvers, enhancing maritime safety and operational efficiency.

The system holds promise for both existing ships and forthcoming autonomous ships, provided that technological limitations akin to those identified in Sections 7.1 and 7.2 are adequately addressed.

7.6. Improvements and future works

This paper acknowledges certain limitations in its data collection methodology. The selection of keywords and the search strategy, though designed to capture the most relevant studies, may have inadvertently excluded significant papers (See Fig. 7). Additionally, relying on a single database (Web of Science Core Collection) constrained the diversity and breadth of the literature review. The manual screening process, despite being thorough, is inherently subjective and may introduce biases, potentially impacting the research outcomes, see Table 1. Furthermore, the paper does not specifically address contacts involving ships and offshore structures, which warrants further attention.

To address these limitations and enhance future research, it is recommended to employ more expansive search strategies and a broader selection of keywords to capture a wider array of relevant studies. Utilizing multiple databases (i.e., Scopus, Google Scholar) would further increase the diversity and comprehensiveness of the literature reviewed. Additionally, adopting automated screening methods could mitigate human error and bias, thereby improving the reliability and inclusiveness of the study findings. Future research should specifically focus on conducting a comprehensive review of advances in contacts involving ships and offshore structures.

8. Conclusions

The paper presents a systematic literature review with the focus on collision and grounding assessment, especially from the viewpoint of intelligent decision support systems for future intelligent ships. Through maritime accident analyses, insights into proactive ship collision and grounding management have been identified, and key engineering science-based methods have been reviewed. The paper focused on aspects of modelling and assessment using both big data analytics and concurrent simulation approaches. Other topics addressed focus on the potential use of risk analysis for damage evaluation and ship motion predictions for proactive accident prevention. The review of these strategic research streams demonstrates the need to “bridge” traditional maritime systems and NG-WTS. Key conclusions can be summarized as follows:

- Despite technology advances, the high number of ship collision and grounding accidents remain prevalent. Unless sufficiently tackled through the introduction of improved risk management frameworks, these unfortunate events may influence the sustainability of maritime operations and coastal communities. This statement is further supported by the emergence of autonomous ships, which require the development of intelligent decision-making systems accounting for both probability and consequence analysis.
- The convergence of digitalization and AI technologies holds the potential to swiftly model ship motions and their resultant damages under real conditions. This facilitates the generation of reliable ship manoeuvring commands aimed at preventing collisions and groundings, thereby enhancing maritime safety. However, the quality and availability of real data streams remain a challenge in terms of implementing such models in intelligent decision support systems. Additional uncertainties with big data management and the cost of computational methods employed can influence adversely real progress in this field.

- An intelligent decision support system, leveraging the synergy of digitalization and AI technologies, can significantly enhance crew decision-making. This proactive risk mitigation tool offers a means to pre-empt human oversight. It also furnishes the optimal strategies for formulating safe ship manoeuvring commands aimed at collision and grounding prevention through extensive iterations and testing.
- Today scientific and engineering progress in ship collision and grounding assessment methods using big data analytics has become increasingly evident. These studies can be used to support decision-making on the ship from a proactive control perspective. However, emerging methods should link with crashworthiness theory to mitigate the influence of real operational conditions on the management of shipping operations. The fundamental objective of this process should be the management of uncertainties.
- The cornerstone of collision and grounding prevention lies in the dependability of key ship engineering systems (e.g., engine, propulsion system, electrical generators) with navigation equipment and the crew under realistic environmental and traffic conditions.

CRediT authorship contribution statement

Mingyang Zhang: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Ghalib Taimuri:** Writing – original draft, Visualization, Validation, Resources, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Jinfen Zhang:** Writing – review & editing, Writing – original draft, Resources, Funding acquisition, Conceptualization. **Di Zhang:** Writing – review & editing, Resources, Project administration, Funding acquisition, Conceptualization. **Xinping Yan:** Writing – review & editing, Data curation, Conceptualization. **Pentti Kujala:** Writing – review & editing, Project administration, Funding acquisition, Conceptualization. **Spyros Hirdaris:** Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Funding acquisition, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. The criteria of the ship type classification

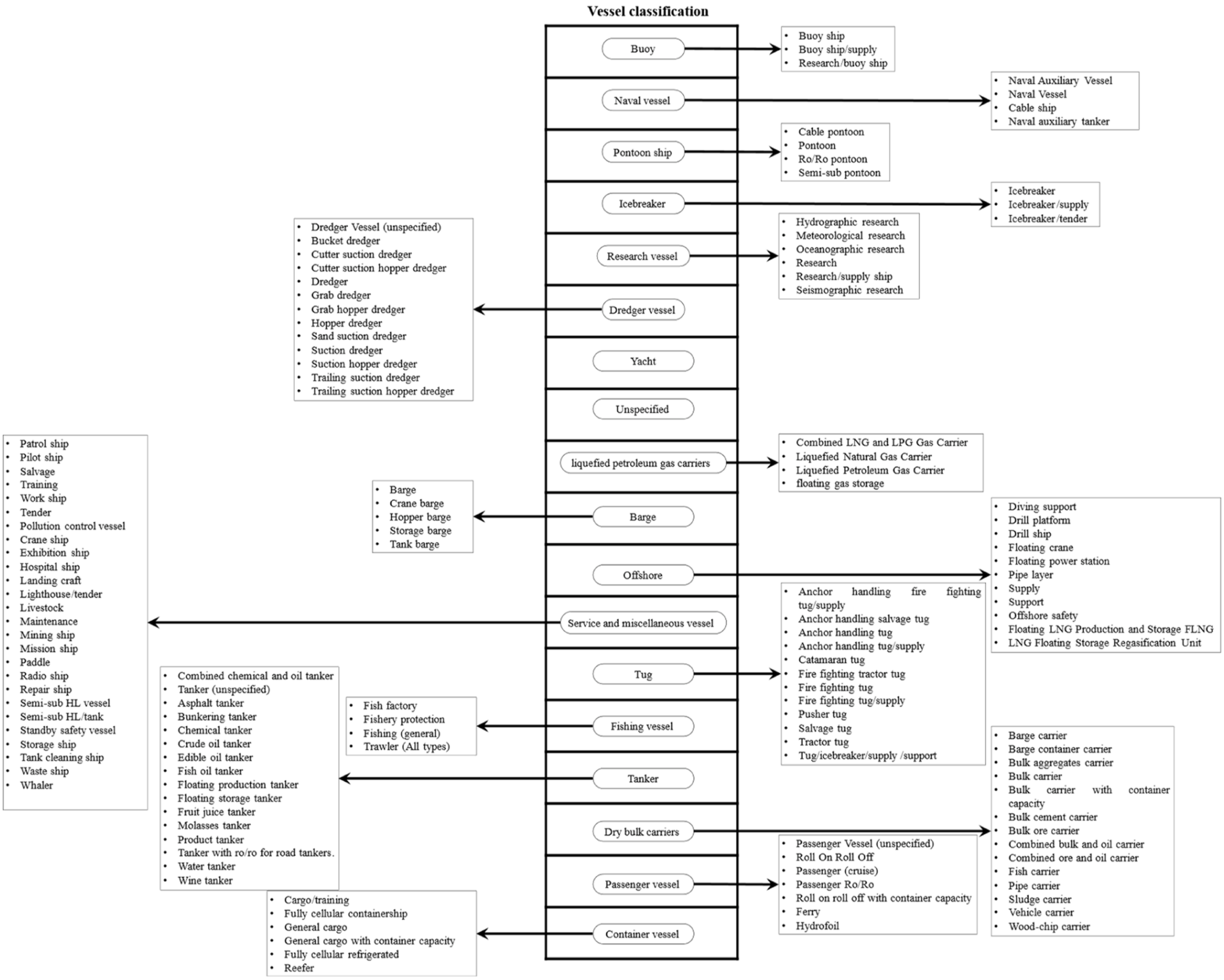

Fig. A 1. Ship type classification.

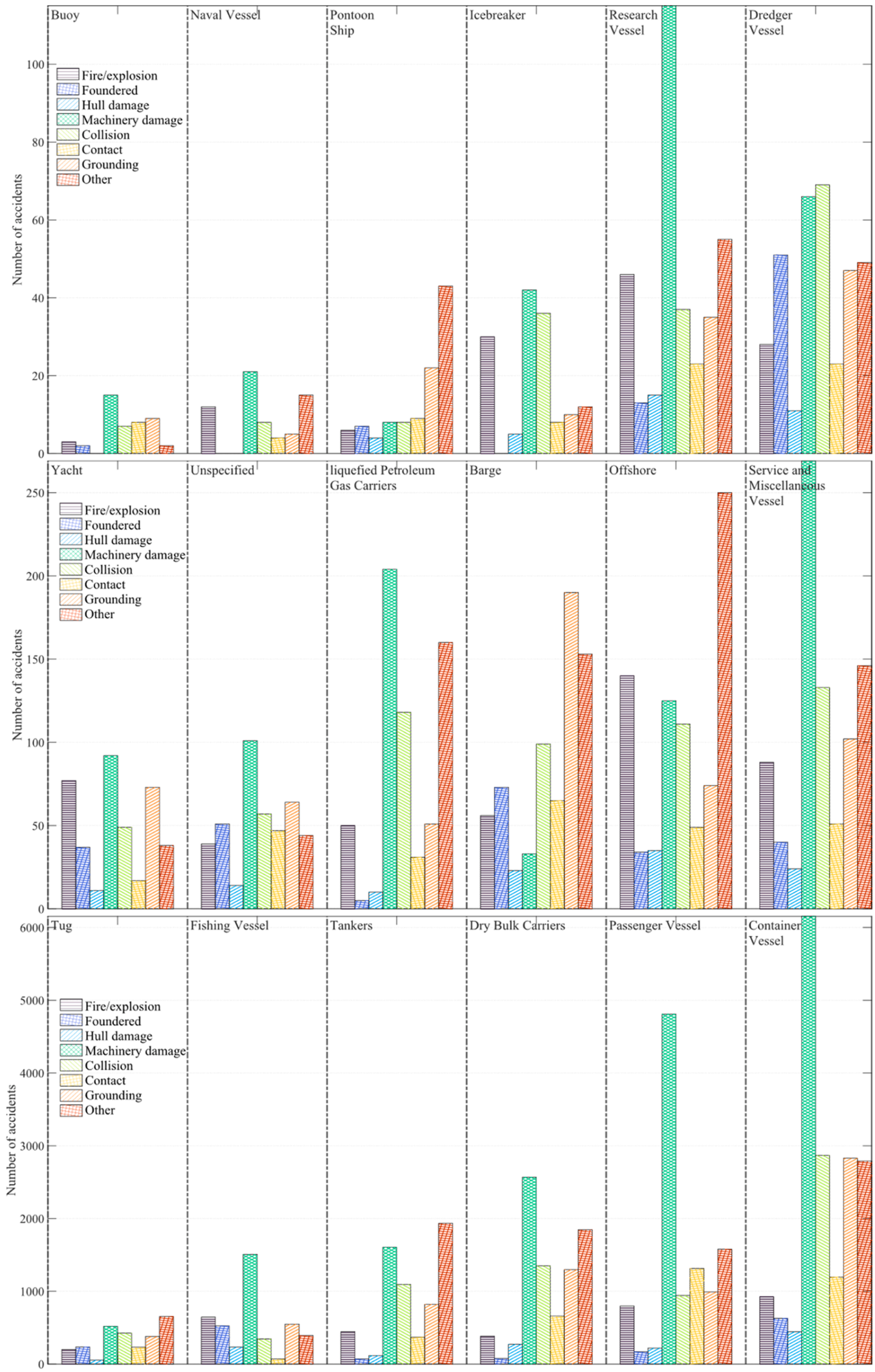

Fig. A 2. Distribution of global maritime casualty events for different ship types over 2002–2022.

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