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Review

New frontiers in the risk assessment of ship collision

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ABSTRACT

Navigation is becoming more and more complex over the years. The increase in maritime traffic and vessel size is inducing a global escalation of ship collision accidents, with consequent losses of human lives and economic assets worth billions. This is particularly true for port basins, with maritime authorities struggling worldwide to keep up with the ever-increasing ship traffic. In this respect, the demand for advanced methods to assess and mitigate ship collision risk has never been higher. The interdependency between physical failures, weather conditions, logistics, governance and human factors requires sophisticated frameworks to effectively assist maritime authorities and navigators in decision-making.

The present work reviews the most recent advancements in the risk assessment of ship collision. The article focuses on new, rising technologies, identifying the current main trends and discussing future perspectives and challenges. The review revealed a wide and diversified range of methods, including machine learning, clustering techniques, swarm intelligence algorithms and others. To frame the methods in the current literature and compare them with previous efforts, they are categorized according to literature classifications. Advancements of well-established approaches and new promising tools are discussed, considering methods that allow the inclusion of quantitative and qualitative variables in the assessment. Furthermore, a comprehensive analysis of a database of maritime accidents in port areas is carried out to investigate prevailing trends in both worldwide and Mediterranean Sea contexts. Results indicate that ship collision accidents constitute the majority compared with other types of accidents, especially in the Mediterranean.

1. Introduction

Navigation in ports has become significantly complex in the last decades. The progressive increment of maritime traffic has determined constantly growing pressures on port spaces (Bellsolà Olba et al., 2020), resulting in reduced maneuverability and a higher probability of close encounters or accidents. Furthermore, the global fleet is also growing in numbers (Perera and Soares, 2017), with a consequent increase of traffic in port accesses and transit areas. In addition, ships are growing in size (Tchang, 2020). Larger ships imply reduced maneuverability and therefore a greater risk of collision, especially in those ports where space is limited by physical obstacles or narrow maneuvering basins. Although conflict avoidance is a priority for many seaport systems, collisions remain the majority of all types of ship accidents to date (Debnath et al., 2011). The number of traffic movements in a port channel can in fact reach, for particularly busy ports, up to 2000 transits per day and this number is expected to increase (Yip, 2008).

Such increase of accidents led the scientific community to focus on the risks of maritime operations, and to question the paradox of having low safety standards within a low-cost transportation system (Kristiansen, 2013). In this regard, risk analysis methods for maritime transport have attracted an ever increasing interest, to the point that international organizations have committed to provide recommendations on the use of specific risk analysis and management tools (IMO, 2018).

However, collision risk in maritime transportation may come from very different types of hazard. Adverse weather, natural disasters, human error, uncharted waterways are just some of the specific threats which may endanger ships, goods, marine personnel, passengers or environment. Moreover, physical and logistical characteristics may differ greatly depending on the specific port, i.e. shape and size of the maneuver basin, traffic density, bathymetry, physical processes, prevalent metocean conditions etc.

All the aforementioned aspects, including the heterogeneity (or lacking) of available accident databases, pushed the safety science

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community to provide advanced tools for collision risk evaluation. In this regard, current literature on maritime risk assessment is thriving at an unprecedented pace, with numerous, new methodologies being developed every year. Nevertheless, they vary widely in terms of required input information, concept, mathematical model, field of application, scientific soundness and uncertainty evaluation tools. The key to any successful risk analysis also passes through the choice of the right method for the examined situation, which influences the accuracy of risk evaluation and the effectiveness of mitigation measures.

In the present work a literature review on ship collision risk assessment methods is presented, in which a range of relevant studies was analyzed and critically discussed. The paper focuses on new, cutting-edge technologies developed in the last decade, to provide an overview on future perspectives and challenges of maritime collision safety evaluation.

Particular attention is given to the risk assessment technologies and their state of the art, by discussing strengths and weaknesses of the employed methodologies. In comparison with previous reviews, which limited only to certain approaches or classified the methods based on the type of input data, herein the goal is to critically discuss the features of the employed technologies, by acknowledging their advancements as well as questioning their effectiveness and applicability. A classification based on technology allows for a deeper understanding of the potentials and limitations of different approaches and can provide guidance on which technologies may be most suitable for a given situation. In addition, a technology-based review can help to identify opportunities for future investments in new or emerging technologies to improve their effectiveness, reliability or cost efficiency.

In order to contextualize the reviewed works within the current literature and allow the comparison with previous studies, they were categorized according to state-of-the-art classifications (Goerlandt and Montewka, 2015b; Chen et al., 2019). Further development of established approaches and new methods are both included in the assessment. Furthermore, a detailed analysis on a database of ship accidents in port areas is presented, to analyze worldwide and Mediterranean trends.

The paper is structured as follows: Section 2 presents a data analysis on maritime accidents in port areas; Section 3 briefly introduces the risk definition adopted in the present work; Section 4 describes the classification methods used to categorize the different methods; Section 5 describes the methodology of the review process; Section 6 illustrates the reviewed literature; a critical discussion on the reviewed methodologies is provided in Section 7; finally, a conclusive chapter (Section 8) closes the work.

2. Analysis of vessel accidents in port areas

Understanding ship accidents distribution in terms of Grosse Tonnage (GT), typical age of the affected vessels, category of the ships, as well as distribution of underlying causes and consequences is the first necessary step to improve accident mitigation strategies.

Collection and analysis of ship accident data allow to identify patterns and trends that can be used to develop strategies for reducing frequency and severity of these accidents. In such an ever-changing scenario, up-to-date databases analyses are of paramount importance to track progress over time and to evaluate the effectiveness of risk mitigation measures. Identifying the type of ships or routes that are more likely to experience collisions, or that certain types of accidents are more common than others, is important as it allows to identify criticalities and opportunities for improvement.

To this aim, an analysis of a database of vessel accidents in port areas is herein presented. The accidents are analyzed in terms of relevant vessel characteristics such as age, GT and segment. Causes and consequences of the available accidents are discussed and a data analysis has been carried out.

The dataset was created starting from the following two databases:

- *SeaSearcher*, which recorded 79,592 vessel accidents between 1967 and second quarter (Q2) of 2021;
- *IHS*, which recorded 23,897 vessel accidents between 1990 and Q2 of 2021.

These two databases were compared considering International Maritime Organization (IMO) identification number, accident date and location (at sea or in port), in order to create a unified database with consistent data. In the event of common accidents found within the system (meaning findings with the same IMO number and the same accident date), the location was compared. If the two locations in the databases were not matching, the accident was not included in the unified database for the analysis. The final database comprises 13,846 accidents worldwide, of which 2799 occurred in port areas and 634 in Mediterranean port areas. Fig. 1 shows the distribution of accidents in Mediterranean's and worldwide port areas by causality event.

The figure shows that the main causes of the accidents in the port areas regard collisions between two different vessels and this cause 31% accidents worldwide and 37% accidents in the Mediterranean area. Details about the weather conditions are unknown for most of the accidents included in the database, but heavy weather conditions results as a major cause of accidents in the port area when weather conditions are specified. The accidents have more or less serious consequences, and may have consequences on human life and on the total or partial loss of cargo, or the vessel itself. Worldwide, 3% of the accidents had consequences on human life while in Mediterranean ports this value increases, with 5% of the accidents having consequences on human life. For both worldwide and Mediterranean analysis, 2% of the accidents have reported a loss of cargo or of the entire ship. The vessel segment that reported more accidents, is the General Cargo, both for worldwide and the Mediterranean, followed by the Passenger Ro/Ro vessels, in the Mediterranean area, and Bulk carrier worldwide. This may be due to the fact that General cargo and Bulk carrier vessels constitute the most significant portion of the worldwide fleet. The range of the vessel's age at the time of the accident that reported more accidents is between the 0–10 years for both the worldwide and the Mediterranean analysis. The ships with a gross tonnage between 500–5.000 GT are more involved in port accidents. This may be due to the large number of ships of the worldwide fleet with a tonnage comprised between 500 and 5.000 GTs. Further details on the data analysis are provided in a freely accessible Mendeley Data repository (Marino et al., 2022).

3. Definition of risk of collision

In the field of risk assessment, there is no univocal definition of risk. This concept has evolved with very different designations depending on risk perspective, risk perceiver and area of application. The Society for Risk Analysis defines "risk" as "the potential for the realization of unwanted and negative consequences to human life, health, property or the environment". According to the definition of IMO, the risk is the result of the combination of frequencies of occurrence and the related severity of the consequences, with the frequencies traditionally defined by means of probability. A quantitative definition of risk, relating to an undesirable event E, and widely used in the maritime sector is the one formulated by (Ayyub, 2003):

$$E = probability(E) \times consequences(E) \tag{1}$$

Probability-based methods to assess risk are generally preferred as they provide quantitative and exhaustive results for both risk evaluation and mitigation, in combination with the estimation of its consequences (Chen et al., 2019). A widely applied probabilistic-risk definition framework is the one proposed by Fujii and Shiobara (1971) for the risk of collision, which is:

$$P_{collision} = P_{geometric} \times P_{causation} \tag{2}$$

According to Eq. (2), the collision probability is divided into two terms: the number of collision candidates, also known as geometric

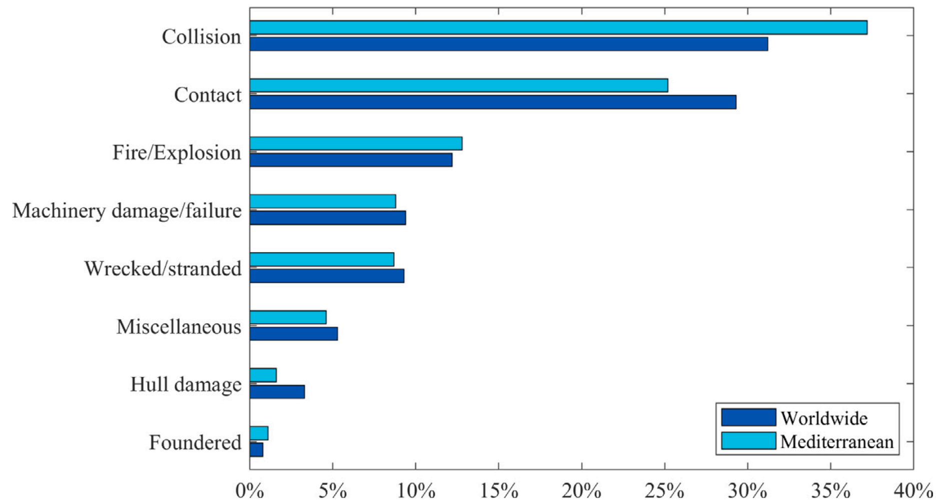

Fig. 1. Distribution of accidents in Mediterranean's port areas by causality event.

probability $P_{geometric}$, which is related to strictly geometrical aspects of the encounter; and the causation probability $P_{causation}$, which includes components related to technical faults, failures, human reliability etc.

4. Classification of maritime risk assessment methods

According to Ozbas and Altiok (2012) risk analysis methodologies on maritime systems can be classified into two groups: (i) quantitative assessment of undesirable events, based on reliability analysis, modeling engineering tools or statistical data analysis; (ii) qualitative assessment, using expert or non-expert judgement,

Quantitative assessments aim at identifying an objective and quantifiable value for determining the components of the system that contribute to the risk. Although they are numerous in literature, their application is weakened by two main issues. First, data on port operations accidents are often incomplete, not available or do not exist at all. In addition, seaport conditions are constantly evolving due to changing traffic patterns, fleet size and environmental conditions. Data that might have been relevant to use, may not be anymore as the port asset is changed in the meantime. Second, accidents that occur with greater probability generate nearly insignificant consequences. On the contrary, severe accidents are generally more rare and quantitative data, even when systematically recovered, are often insufficient to obtain robust quantitative (e.g. statistical) analyses. Therefore, qualitative methods are of critical importance in those cases in which data availability is limited (Apostolakis, 1990).

According to Goerlandt and Montewka (2015b), three different approaches on the analysis of maritime risk can be distinguished: realist, constructivist and proceduralist approaches. Risk realists generally view risk as a physical attribute of the system, which can be defined by objective facts, and therefore controlled and predicted. These methods make use of quantitative information related to events and their relative consequences. On the other hand, risk constructivists generally consider risk as a social construct, which is attributed by risk-perceivers to a technology or a system, rather than being a physical part of it. Under this assumption, risk analysis depicts a mental/social construct of a group of assessors, which can be experts and/or non-experts. Finally, risk proceduralists lie halfway, i.e. risk is characterized through an integrated understanding of the whole system, balancing objective facts and perceived values, making use of both quantitative and qualitative data sources.

These three views are furtherly subdivided in the following approaches, which are schematized in the following:

(i) **Strong Realist** (SR) risk is factual and exists as an objective feature of the system, therefore risk analysis represents an estimation of a quantifiable physical attribute. The evaluation is based exclusively on data collected from the system or derived from engineering models; judgement of assessors, both experts or non-experts, is not considered. In this case, data regarding the uncertainty of the assessment is not provided. Stakeholders are generally not involved in the evaluation process.
(ii) **Moderate Realist** (MR). Analogous to the strong realistic approach, is largely based on quantitative data and on engineering models. Assessors' judgement is considered, however non-experts are excluded and generally used as completion data. Uncertainty of evidence may be included.
(iii) **Moderate Realist with Uncertainty assessment** (MRU). Similar to the moderate realist approach but provides uncertainty assessments of results.
(iv) **Scientific Proceduralist** (SP) It is based both on quantitative data and/or engineering models, and on the judgement of assessors (both experts and non-experts).
(v) **Moderately Constructivist** (MC). Risk is a mental construct and risk analysis is described by its features as experienced by risk perceivers. It is based on both quantitative data and expert judgement. Risk assessment uncertainty is not evaluated and stakeholders are not involved in the evaluation process.
(vi) **Precautionary Constructivist** (PC). Similar to moderate constructivist, although separation between facts and non-epistemic values is considered relevant.
(vii) **Constructivist** (C). Similar to the moderate constructivist, evidence uncertainty may be considered.
(viii) **Strong Constructivist** (SC). Risk is analyzed as a mental construct, which involves primarily perceptive attributes. It is mainly based on the judgement of non-expert people, who can be informed by the judgement of experts. Uncertainty of evidence values may be considered.

Chen et al. (2019) developed a classification structure based on modeling aspects and parameters used to quantify risk. The categorization focuses on both technical features of the methods and the stakeholders to which they are specifically addressed.

(i) **Synthetic Indicators** (SI). They describe geometric risk probability by simple dimensional parameters, this includes Closest-Point of Approach (CPA), Distance to CPA, Time to CPA etc.
(ii) **Safe Boundary Approach** (SBA). These methods evaluate collision risk based on the superposition of ship domain and collision diameters

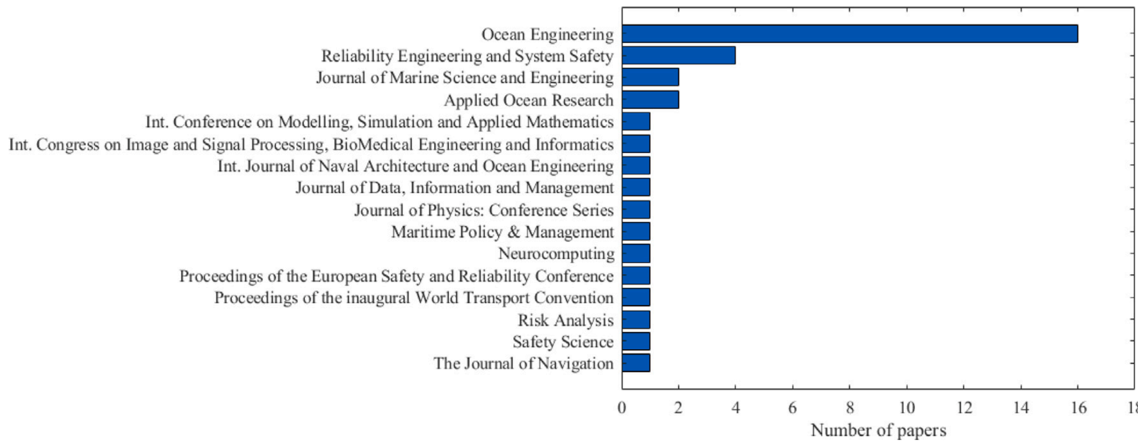

Fig. 2. Number of reviewed papers per journal.

(iii) **Velocity-based Approach** (VA). Distances and velocities of collision candidates are presented in a velocity space and corresponding patch shadow area of the possible routes and consequent potential areas of impact.
(iv) **Statistical Analysis Approach** (SAA). Probabilistic analysis based on time series of accident datasets to investigate human and non-human factors in risk collision.
(v) **Fault Tree Analysis** (FTA). Inferential analysis of failure reports based on a deductive process using simple binary Boolean logic operators
(vi) **Bayesian Approach** (BA). Complex inference network with conditional probability operators to model multi-state causation relationships between contributing factors

5. Review methodology

An extensive literature review was carried out by using field-related keywords such as *maritime safety, probabilistic risk analysis, ship–ship collision, maritime accident* etc. A total of 50 papers were collected. The selection of papers was then narrowed down based on the following criteria: (i) maritime ship collision risk only, either considering ship–ship or ship–structure collision; (ii) year of publication (>2016); (iii) papers not previously reviewed in other literature reviews; In the end, 36 papers from indexed journals and conferences were considered in the review process, those papers, their methodology and classification according to Goerlandt and Montewka (2015b) and Chen et al. (2019) are shown in Table 1. Fig. 2 shows the distribution of the papers per journals, with *Ocean Engineering* being the reference journal for ship collision risk assessment. Finally, Fig. 3 illustrates the distribution of the reviewed papers according to Goerlandt and Montewka (2015b) and Chen et al. (2019), showing a large majority of Strong Realist (71%) and Synthetic Indicator Approach (50%) methodologies.

6. Review of risk analysis methods

The methodologies to assess ship collision risk are discussed herein. New technologies alongside well-established approaches are included, analyzing the most recent advancements from past literature and providing a glance on future perspectives. Rather than following the aforementioned classifications, the reviewed methods were broken down by technology, in order to easily introduce the basics and discuss perspectives and challenges of each methodology.

6.1. Geometric indicators approaches

Geometric Indicators Approaches (GIAs) consist in the calculation of dimensional quantities related to ship position and velocity, which allow to define potential risk based on geometric parameters. One of those GIAs is the Synthetic Indicators approach. Synthetic indicators are quantities that describe the distribution in space and time of a potential encounter. A widely used method is the Closest Point of Approach (CPA) and its related parameters: Distance to CPA (DCPA), which means the closest distance between two ships and Time to CPA (TCPA), which is the time left to the CPA point (Fig. 4a). Synthetic indicators reflect the projected spatio-temporal encounter scenario assuming that every ship maintains speed and route over the whole potential conflict. The methods that employ CPA can provide a quantitative risk estimation of the probability of occurrence, which can be implemented in radar systems or into a navigation aid systems (Bukhari et al., 2013; Wang et al., 2017).

Thanks to their simplicity, these methods won a certain popularity in the last decades (Mou et al., 2010; Debnath and Chin, 2010; Goerlandt et al., 2015; Zhang et al., 2015; Zhen et al., 2017). However, their application is limited to the collision risk between one Own Ship and one or more Target Ships, making the method generally unsuitable to model multiple ship encounters.

A step forward in this sense was done by Rong et al. (2019), who developed a model based on risk synthetic indicators, TCPA and the relative distance between ships, to obtain collision risk maps. Three-month Automatic Identification System (AIS) data were used to identify 1671 near collision scenarios off the Coast of Portugal, with 827, 384 and 460 being overtaking, crossing and head-on collision scenarios, respectively. They adopted the Kernel Density Estimation method to obtain maps of near-collision. The analysis of the maps showed overtaking collisions occur more frequently along the main shipping routes, whereas crossing and head-on near collisions tend to occur at junction areas.

More recently, Rong et al. (2022) proposed a novel approach to identify risk ship collision using synthetic indicators and a Sliding Window Algorithm. This algorithm is formed by a “window” that can slide along the data to capture different portions of them (Keogh et al., 2001). The authors use this algorithm to identify the ship trajectory. In particular, it allows to obtain better performance in trajectory feature extraction compared with other algorithms due to its efficacy to identify the ship’s situational information in near-collision scenarios. They used three-month AIS data to identify 2846 encounter scenarios off the coast of Portugal. However, AIS data are not synchronized at the same time. To overcome this limitation, the authors adopted a

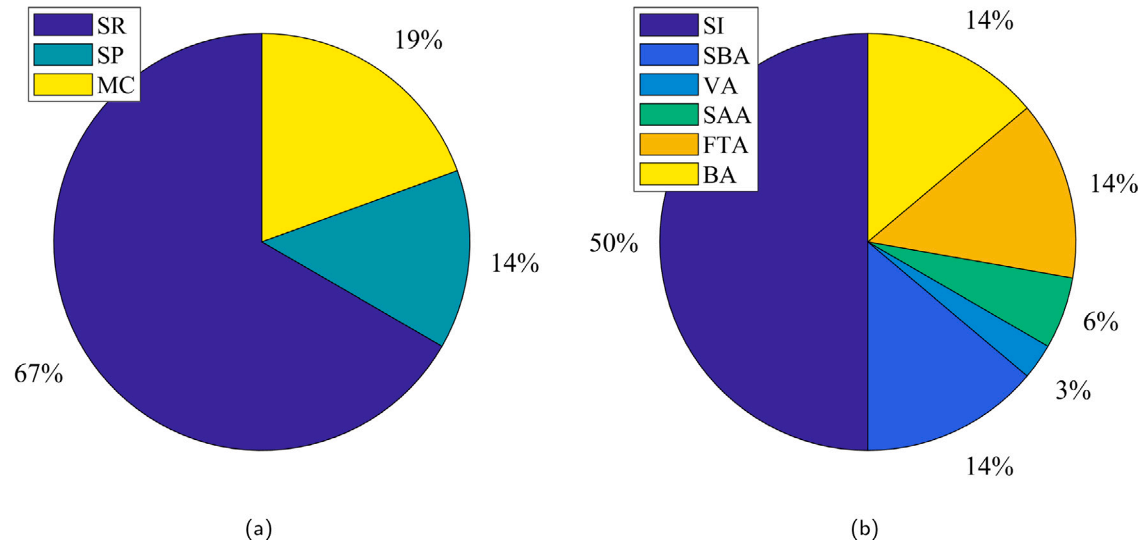

Fig. 3. Classification of the reviewed papers according to: Goerlandt and Montewka (2015b) (a), and Chen et al. (2019) (b). SR = Strong Realist, SP = Scientific Proceduralist, MC = Moderately Constructivist, SI = Synthetic Indicators, SBA = Safe Boundary Approach, VA = Velocity-based Approach, SAA = Statistical Analysis Approach, FTA = Fault Tree Analysis, BA = Bayesian Approach.

Table 1
Reviewed articles and their classification following Goerlandt and Montewka (2015b) and Chen et al. (2019).

Article	Methodology	Classification according to Goerlandt and Montewka (2015b)	Classification according to Chen et al. (2019)
Arici et al. (2020)	Fuzzy bow-tie risk analysis	MC	FTA
Aydin et al. (2021)	Fuzzy Bayesian network	MC	BA
Chen et al. (2021)	Velocity obstacle	SR	VA
Fan et al. (2020a)	Tree augmented network	SR	BA
Feng (2019)	Convolutional Neural Network	SP	SI
Hu and Park (2020)	Fuzzy logic and Analytical Hierarchy Process	SP	SI
Hu et al. (2020)	Fuzzy C-means algorithm	SR	SI
Jiang et al. (2020)	Bayesian Network	SR	BA
Li et al. (2018)	Adaptive Fuzzy Neural Network	SR	SI
Liu et al. (2020)	Recurrent Neural Network	SR	SBA
Liu et al. (2022)	Safe domain and SVM	SR	SI
Ma et al. (2022)	HFACS, DEMATEL model and Fuzzy Cognitive Map	SR	SAA
Namgung et al. (2019)	Closest point of approach and ANN	SR	SI
Qiao et al. (2020)	Dynamic fuzzy Bayesian network	MC	BA
Rong et al. (2019)	Closest point of approach	SR	SI
Rong et al. (2022)	Closest point of approach	SR	SI
Sakar et al. (2021)	Fault-tree analysis and Bayesian network	SR	FTA
Ziqiang et al. (2022)	Fuzzy logic and Analytical Hierarchy	SR	SI
Silveira et al. (2021)	Multi-criteria decision approach	MC	SI
Sokukcu and Sakar (2022)	Fault-tree analysis, Bayesian network and Fuzzy logic	MC	FTA
Ugurlu and Cicek (2022)	Fault-tree analysis	SR	FTA
Ung (2019)	Fault-tree analysis, Bayesian network and CREAM model	MC	FTA
Wang et al. (2016)	Analytical Hierarchy Process and ANN	SP	SI
Wu et al. (2019)	Fuzzy logic	SR	SBA
Xie et al. (2019a)	Beetle Antennae search algorithm	SR	SI
Xie et al. (2019b)	Q-learning beetle swarm antenna search	SR	SI
Xie et al. (2020)	Long short-term neural network and Q-learning	SR	SI
Yıldırım et al. (2019)	Human Factors Analysis and Classification System	SP	SAA
Yoo and Lee (2019)	Closest point of approach	SR	SI
Yu et al. (2021)	Bayesian network and Evidential Reasoning	SP	BA
Yu et al. (2022)	Multi-criteria risk assessment	MC	SI
Zhang and Meng (2019)	Critical ship safety distance	SR	SBA
Zhang et al. (2020)	Convolutional Neural Network	SR	SBA
Zhen et al. (2022a)	Multi-ship encounter arena model	SR	SI
Zhen et al. (2022b)	Multi-ship encounter model	SR	SI
Zheng et al. (2020)	Support Vector Machine	SR	SBA

cubic spline interpolation. They calculated TCPA and DCPA to identify near-collision scenarios. In particular, the majority of encounter scenarios are represented by overtaking scenarios. Also, the analysis of results indicates that 47.5% of ships took evasive maneuvers in crossing scenarios.

Another geometric indicator approach is the safe boundary. This is based on areal boundaries that reflect spatial relationships between potentially colliding ships. Among these, collision diameter and ship domain are the most relevant concepts used in the field. Fujii and Tanaka (1971) defined the ship domain as “a two-dimensional area

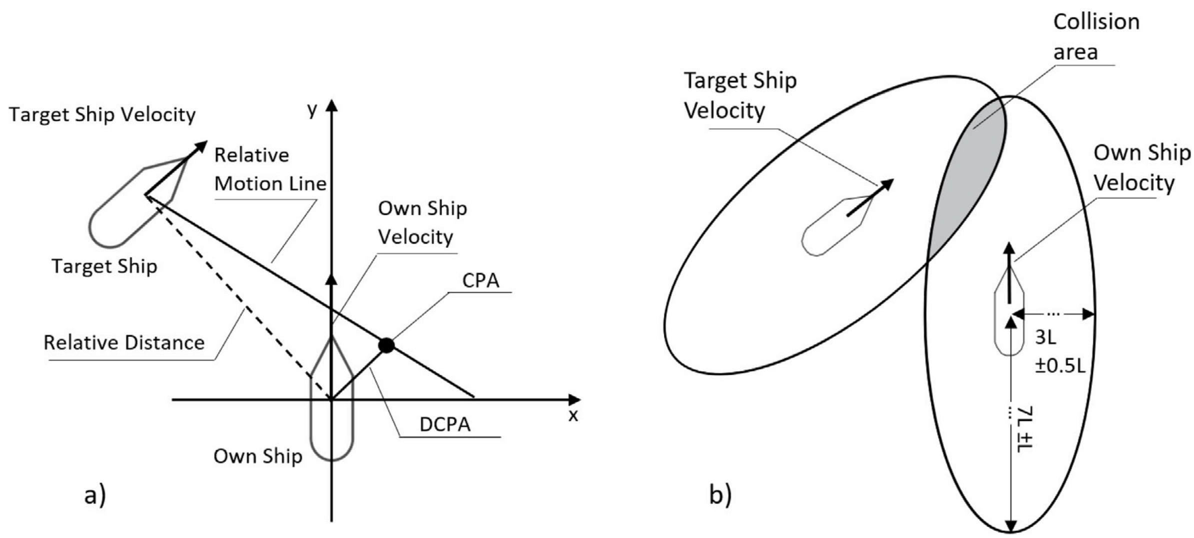

Fig. 4. Schematization of Closest Point of Approach (a) and Safe Domain (b) where L is vessel length.

surrounding a ship which other ships must avoid — it may be considered as the area of evasion" (Fig. 4b). Analogously to the synthetic indicators, the one of safe boundary is a well-established approach in the practices of ship collision risk analysis (Montewka et al., 2010; Qu et al., 2011; Montewka et al., 2012; Goerlandt and Kujala, 2014; Baldauf et al., 2015), as it offers a concise and fast procedure to identify collision scenarios. However, it is known to be very sensitive to parameter settings and can provide significantly different outcomes for the same encounter case. Moreover, in the concept of safe domain, the perimeter of the safety area is a crisp boundary, sharply separating safety and risk conditions. In reality, boundaries of the safe area are uncertain due to the behavioural conduct of navigators.

To overcome this limitation, Zhang and Meng (2019) developed a model based on a probabilistic safe domain, i.e. the safe domain boundary is computed as a probabilistic value based on the distribution of the target ships. One-week AIS and ship characteristics were used as input data. A Gaussian kernel is employed to estimate the probability of the boundary of the domain. The authors compared this domain with the traditional ones: Fujii's domain (Fujii and Tanaka, 1971), Goodwin's domain (Goodwin, 1975) and an empirical domain based on AIS data (Hansen et al., 2013). Results show that the boundaries of the probabilistic domain is generally more conservative, including the Fujii and Goodwin's domains.

Another study based on safe boundary approach was conducted by Yoo and Lee (2019), which introduced a Collision RIsk model (CoRI) based on the vessel traffic service operators' and navigator's awareness of ships encounter conditions. They compared this model with the one used by Korea Maritime Safety Audit based on Environmental Stress (ES). ES is a model based on judgements of the navigator about the risk level and it does not take into account ships encounter conditions. Indeed, ES tends to overestimate the risk. In order to improve the model, the authors introduced a CoRi model which evaluates the risk by considering the distance from the ship domains and the CPA, the time for avoidance maneuvers and the potential encounter of ships at CPA. Using one-year of AIS and RADAR data of the port of Busan (South Korea), the authors compared those models for three collision scenarios: crossing, head-on and overtaking. In contrast with CoRI, the ES model does not consider ship velocity in the assessment. Results showed that the ES model tends to highly overestimate risk with respect to the CoRI model.

Zheng et al. (2020) proposed a probabilistic approach, in which the ship domain is considered as a point cluster and used as input in a Support Vector Machine (SVM). SVM is a deep learning algorithm that carries out risk minimization by maximizing the margin between two clusters. SVM accomplishes the task by constructing an optimal hyperplane that better separates data clusters. In contrast with the conventional methods based on ship domains, SVM can estimate a quantitative and continuous probability of the risk by taking into account the states of ships, their relative position and their velocity. The points of the boundary of domains are used as input data to train the SVM. Three ship collision scenarios were carried out: head-on, crossing and overtaking. Results showed that head-on scenario is the most critical one and the overtaking scenario is the safest one. They compared these results to the results derived from traditional methods such as DCPA, TCPA and Spatial Collision Risk (SCR) model, showing that SCR does not take into account the overlapping of ship domains, and it underestimates the probability of collision in all scenarios.

More recently, Liu et al. (2022) proposed a novel approach based on ship domain able to quantify the collision probability and to define the consequences. They introduced two additional parameters: the maximum interval and the violation degree of two ship domains. The first parameter is used to evaluate the collision risk of two ships and it is usually based on geometric equations, however it is not suitable for ship domains composed of irregular curves. To overcome this limit, in this study, the authors applied SVM to obtain the maximum interval of two ships. The violation degree is the ratio of the intersection area between two ship domains to the sum of their individual areas. Head-on, crossing and overtaking scenarios were carried out. Analogously to the results found by Zheng et al. (2020), this study showed that the maximum collision probability is obtained during the head-on scenario and the safest scenario is the overtaking one.

6.2. Artificial neural networks

Artificial Neural Networks (ANNs) are mathematical models characterized by structures and calibration processes that can map complex relationships between variables by reproducing the human neural network (Abiodun et al., 2018). ANNs are widely used in many research areas thanks to their suitability to parallel computing and the possibility to store information on the network. They are widely used in the forecasting of events. For instance, ANNs are applied to forecast sea states (Duan et al., 2020; Fan et al., 2020b; Ma et al., 2021) and storm surge (Kim et al., 2019; Qiao and Myers, 2022). However, in contrast with other machine learning models such as SVM, they are usually described as "black boxes", i.e. they capture the hidden relationships between inputs and outputs with a highly accurate approximation, however why or how they find a solution it is unknown (Foresee and Hagan, 1997).

Different types of ANNs were developed since their invention. Convolutional Neural Network (CNN) is composed by convolutional, pooling and fully-connected layers (O'shea and Nash, 2015). Each layer is comprised of neurons organized into three dimensions, the spatial dimensionality of the input (height and width) and the depth. The depth refers to the third dimension of an activation volume and it is defined by the number of filters contained in the convolutional layer, which aim is to detect features of data. The aim of the pooling layer is to reduce the complexity and the dimensionality of the model. Lastly, fully-connected layers contain neurons that are connected to the ones of convolutional and pooling layers, which aim is to perform the same duties of a standard ANN.

The application of ANNs in maritime risk assessment is not recent (Lisowski et al., 2000; Simsir and Ertugrul, 2009; Simsir et al., 2014; You and Rhee, 2016). However, up to now the ANNs have been used only for forecasting the future position of the ships, in order to avoid the collision, and not for the evaluation of risk indices. In this sense, a development of ANNs in collision risk assessment was done by Feng (2019), which built a CNN based on AIS data and experts' judgements to assess the multi-ship collision risk in the Baltic Sea. In particular, firstly they calculated the initial regional vessel collision risk analyzing the risk factors by taking into account the characteristics of ships and their distance, then the experts revised those values, and the revised data and traffic images were used as input data of the CNN. They used 90% of input data for the training phase and the 10% for the testing phase. They also used a k-means algorithm (Likas et al., 2003) to divide the test samples into seven clusters. The k-means is a clustering algorithm that divides the dataset into pre-defined clusters where each data can belong to only one group. For each cluster the collision risk was calculated, and the mean absolute error was computed to validate the model. In particular, the model demonstrated an excellent performance between the real collision risk and the model results. The authors established different depths of the CNN to test its effectiveness and they found that the mean absolute error decreases as the CNN depth increases.

Similarly to Feng (2019) and Zhang et al. (2020) adopted a CNN to classify ship collision risk levels (Fig. 5). Specifically, the application of CNN allows to mimic experts' judgements of actually risk levels. The authors converted three-month AIS data of the Baltic Sea area into traffic images and built two model of CNN: in the first one they used only the traffic images as input data and in the second one they used both traffic images and ship navigational information as inputs. Analogously to Feng (2019), for the training phase, 90% of data were used whereas the remaining 10% was employed for the validation phase. The aim of this study was to build a model able to classify multi-ship encounter situations by assigning risk levels by assessing the risk. The analysis of the performance of the CNN shows that when the depth of the CNNs increases the predictive accuracy of the model increases as well. However, analogously to overfitting, the excess of filters and, consequently, the increase of the depth, determines a decrease of the performance of the network. The second model that uses traffic images and navigational information is used to improve the predictive performance of the model.

Another type of ANN is the Recurrent Neural Network (RNN). The RNN can send information over time steps and the cyclic connections between its layers can enhance training in the temporal domain and exploitation of the sequential nature of the input. RNN generates outputs where the predictions at each time step are based on current input and information from the previous time steps (Kumaraswamy, 2021). However, ANNs required large memory space and high learning time. With the aim of overcoming these limitations, Xie et al. (2020) combined an asynchronous advantage actor–critic (A3C) algorithm, a Long Short-Term Memory (LSTM) neural network and Q-learning to evaluate multi-ship collision risk. LSTM is a particular type of RNN. In this network the neurons have different gates that can memorize or forget information (Van Houdt et al., 2020). When the value of the forget gate is equal to 1, the information are accepted; meanwhile, a value of 0 means it rejects all the information. Q-learning and A3C are reinforcement learning algorithms, both based on Markovian domains (Pinsky and Karlin, 2011). A Markov process is a stochastic process in which the probability of a known process that is transitioning to a next state depends only on the current state and its past behavior does not alter this probability. In particular, the Q-learning learns only from actions and experienced rewards (Azoulay et al., 2021); whereas the A3C algorithm works with multiple learning agents, which work in parallel with different cases within their respective environments (Mnih et al., 2016). Xie et al. (2020) proposed this combined model in order to improve the standard learning methods that have low learning efficiency issue in terms of computational time and memory costs. The authors compared the combined model with the original A3C method, simulating the encounter of four ships. The analysis of the results reported that the composite model has better performance than the original A3C in terms of speed and optimization. Specifically, in the composite model, after 200 epochs the collision avoidance trajectories are more stable in terms of mean sum rewards. An epoch means training the neural network with all the training data for one cycle.

6.3. Bayesian networks

Another machine learning method that is widely used is the Bayesian Networks (BNs) approach. BNs are graphical inference models which provide a straightforward way to apply Bayes Theorem to complex problems, that can be used for a wide range of tasks in diagnostics and anomaly detection. They are formed by directed acyclic graphs, called nodes, that represent the random variables, and directed arcs, which represent casual or influential relationships between the variables. If a directed arc links a variable A to a variable B, then A is called parent node and B is called child node which means that A causes B. For each node in the graph, a set of conditional probability distributions is associated, that means that the distribution of a variable is defined for every possible outcome of the preceding nodes.

Thanks to their openness and flexibility in incorporating multiple sources of information (e.g. expert knowledge, stochastic simulation results, historical data), they are effective to model multi-state and non-linear causation relationships between accident contributing factors. On that note, their application in maritime risk field is not new (Hänninen and Kujala, 2012; Martins and Maturana, 2013; Montewka et al., 2014; Goerlandt and Montewka, 2015a; Sotiralis et al., 2016). However, the complex dependency relationships between contributing factors may create issues during the construction of the BN, especially if data are scarce. Indeed, when the number of probability parameters increases, the model complexity increases as well (Hänninen, 2014).

A step forward in this sense was done by Jiang et al. (2020), which proposed a ship collision risk analysis method based on a BN built with a K2 algorithm. K2 is a score-based algorithm which considers an ordering of variables as input and assume a random order of variables (Behjati and Beigy, 2020). The application of K2 algorithm avoids the ambiguous relationships that may occur during the construction of the BN. They collected historical accident data along the main route of the Maritime Silk Road (e.g. accident type, ship type, ship age) that occurred from 2017 to 2020 from IMO database and natural environment data (e.g. wind speed, visibility, fog) from Remote Sensing Systems. The authors used the expectation–maximization algorithm to learn the parameters, which find the maximum likelihood parameters and its aim is to estimate the missing data of a dataset by using the available observed data (Do and Batzoglou, 2008). The authors identified the influencing factors of maritime accidents and conducted a sensitivity analysis, to measure the mutual dependence between two variables and how much information can be obtained from a variable by observing the other one (Cover and Thomas, 2005). Also, three-scenario simulation were carried out. The first one assumed different accident types such as collision or contact. Results showed that collision

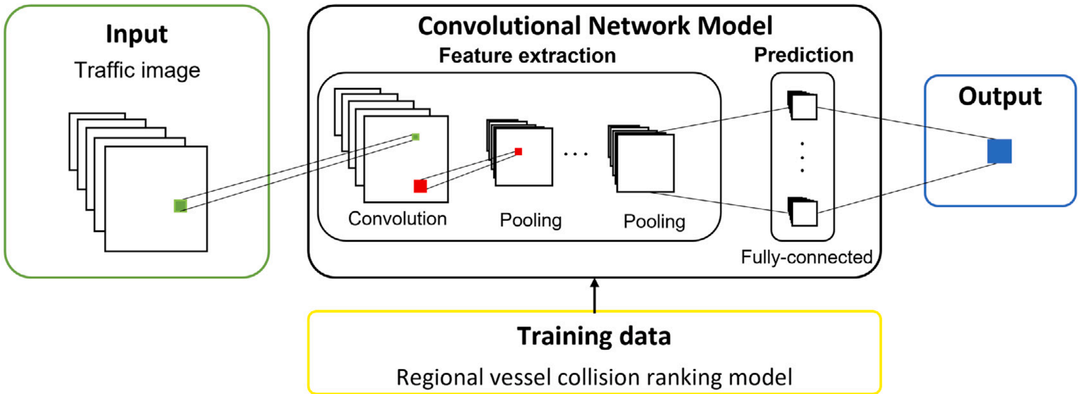

Fig. 5. Convolutional Neural Network collision risk model layout (after Zhang et al. (2020)).

accidents are the most significant one. The second scenario is placed in various locations (ports, sea, waterway). In the last one, several types of ships are considered and they found that tankers and bulk carriers are exposed to higher risk than passenger or container ship.

A few applications of BN use only quantitative information, without integrating e.g. experts/non-experts' judgements. For instance, Fan et al. (2020a) proposed a BN based on a tree structure (called Tree Augmented Network), in which a parent node is connected to all child nodes and each child node can have another child node as parent (Wang and Webb, 2002). In particular, they used a data-driven method to build the model in order to involve less subjective causal relationships. The authors used the BN to investigate how human factors influence maritime accidents. They used the 2012–2017 accident reports from Marine Accident Investigation Branch (MAIB) and Transportation Safety Board of Canada to build the BN. The aim of the network was to find the relationships between risk influencing factors (RIFs) and the data. 25 RIFs were found as variables and a sensitivity analysis is conducted with different approaches: mutual information, joint probability and true risk influence to explain how much strong the relationship between RIFs and the typology of accident is. Finally, the authors simulated the past maritime accidents to validate the BN.

6.4. Multiple-criteria decision analysis

Multi-Criteria Decision Analysis (MCDA) is employed in highly complex decision-making contexts. It is a comparison procedure that aims to find the best solution among different options based on multiple, often conflicting, criteria. In other words, the MCDA tries to rationalize the process of choice by optimizing a set of multiple criteria, weighted according to some priorities. With this analysis, all the information, consequences and the perspectives linked to a possible choice that satisfies the criteria are highlighted.

Thanks to its advantages (e.g. adaptability to slight changes of the input data, ability to take into account uncertainty), MCDA is used in various research fields, including ship collision risk assessment (Arslan and Turan, 2009; Zaman et al., 2012; Wang et al., 2013; Karahalios, 2014; Sahin and Senol, 2015). However, criteria may generate conflicts with each other due to the different experts' opinions that surface different alternatives and criteria. Also, these methods are not easy to compute when many variables are considered.

Some of the most used techniques are Analytical Hierarchy Process (AHP) and Elimination Et Choix Traduisant la REalité (ELECTRE) methods. AHP is a multi-criteria decision-making developed at the end of the 70s. Through pair comparisons, it generates priorities for the alternatives and for the criteria used in the judgement of the alternatives. Also, it summarizes the judgements of the criteria and of the alternatives in order to obtain a global judgement that represents a rational decision able to best achieve the large number of objectives of the decision-maker (Khaira and Dwivedi, 2018).

An example of AHP applied in ship collision is the study of Wang et al. (2016), which proposed a method based on AHP and an ANN. They based their work on Simsir et al. (2014) study and, in order to improve the previous study, they added environment factors, such as the influence brought by the relative movement speed of two ships and the traveling weather, in the calculation of the prediction time. Then, a group of experts identified six factors that played an important role in maritime traffic: visibility, traffic density, weather, experience, draft and the length ratio. For each of them, the authors used the AHP method to calculate the weights of each factor. From this analysis, the authors found that the weights of visibility and experience are the higher. Moreover, the authors included an ANN using AIS data as input in order to predict the position of ships after calculating the predicting time through the proposed algorithm. The predicting time is related to an environment factor that consider the ships' speed and direction, weather condition, length ratio. Then, the collision risk is evaluated using the synthetic indicator DCPA and for each value of collision risk, a risk level is associated. To validate the proposed algorithm, the authors compared it with a three-minute prediction algorithm and calculated the Mean Square Error. The low value of the Mean Square Error showed the accuracy of the proposed algorithm to predict the position of ships and to alarm the drivers well in advance.

The other most used technique is the ELECTRE (Benayoun et al., 1966) method, that is an outranking method based on concordance and non-discordance concepts. It is composed by two phases: aggregation and exploitation. In the first phase, the concepts of concordance and non-discordance are used to make pairwise comparisons of the alternatives and different outranking relations are built. Four preference situations concerning the pairwise comparison can be handled: indifference, strict preference, weak preference and incomparability (Figueira et al., 2013). In the first one, the alternatives are equivalents; strict preference situation means that one of the alternatives is favored over the others for clear and positive reasons; weak preference situation means that one of the alternatives is favored over the others, but the reasons are insufficient to deduce the strict preference or the indifference and incomparability means that the previous situations are not possible. In the exploitation phase, the outranking relations are exploited and the main problem in this phase is to find adequate ways to treat the intransitivity and incomparability of the alternatives. Each exploitation procedure is adapted to three problems: choosing, sorting and ranking and the family of ELECTRE methods provides different methods to solve these problems. For example, an ELECTRE Tri-nC method is used for sorting problems in which, for each pre-defined category, alternatives are assigned (Govindan and Jepsen, 2016).

An example of application of the ELECTRE Tri-nC to assess the ship collision risk is presented by Silveira et al. (2021), in which they considered only judgements' experts. The application of ELECTRE Tri-nC allows to sort the risk in various risk categories and to consider the risk as a decision problem. The experts found the most relevant criteria of collision risk (e.g DCPA, TCPA, wind and sea conditions, visibility, daylight, ships dimensions, bow crossing) and for each of them, they gave a weight in order to rank the criteria. The encounter scenarios were assigned to three risk categories (High Risk, Medium Risk and Low Risk) using ELECTRE Tri-nC (Almeida-Dias et al., 2010) to validate the model. The validation phase was performed by a group of experts involved in the development of the model and by another group that did not develop the model. The analysis of the results reports that 28 of the 30 encounter scenarios were classified in the same risk category by both groups of the experts. For the two remaining scenarios, the group of experts assigned two possible categories where one of them coincided with the other group of experts. That has demonstrated the good accuracy of the model that can easy reflects the experts' judgements.

Another MCDA method is the Evidential Reasoning (ER) approach, which is used within problems having both quantitative and qualitative nature under uncertainties (Xu and Yang, 2001). It consists of hierarchical evaluation model and synthetic rules of Dempster–Shafer evidence theory (Gros, 1997), which is related to the Bayesian probability theory. In particular, the decision problem is modeling by using a belief decision matrix, in which the decision makers preferences are included. Then, the various belief structures are transformed into unified belief structure defined by a set of evaluation grades for qualitative attributes and by numbers for quantitative attributes (Xu, 2012).

Yu et al. (2021) used a BN and an ER to develop a ship risk model. In order to improve the construction of the BN, the ER was applied. It is able to assigns weights to the input data and then, to reduce the size of them. Two-month AIS data were used to identify the ship trajectories off the Coast of Portugal and, also, one year of Port State Control inspection data and experts' judgements were used as input data. Moreover, the relevant RIFs are identified to develop a dynamic risk model based on dynamic information such as ship position and speed. Then, two kind of risk models are studied in that paper: static and dynamic ones. The static risk model is based on ship characteristics. The overall risk model combined these risk inputs into a BN. The validation of the BN is studied with an ER approach. The results obtained with this approach were similar to the BN's ones. In particular, off-route ships, ship type and ship are the most important RIFs.

A development of Yu et al. (2021)'s work was done the following year by the same authors. Yu et al. (2022) studied the ships collision risk in real-time using MCDA techniques. In particular, they combined different methods, such as AHP and ER, to implement a real-time multi-criteria risk evaluation approach that considers both the geometric indicators and the navigational environment. One-day AIS data off the Coast of Portugal were used to calculate indicators such as DCPA and TCPA in order to find the potential collision candidates. Then, different scenarios under different environmental conditions were developed and, considering the experts' judgements, a range of rules and their thresholds are generated in order to define the assessment criteria. For each rule, the experts assigned a weight and the AHP method is used to validate the reliability of the judgements. Also, the authors used an ER to calculate the collision risk in three different encounter scenarios: crossing, head-on and overtaking. Results showed that the collision risk depends on ships' static state and encounter situations, in particular the ship collision risk associated to the overtaking scenario was the highest one. To validate the proposed model, the authors compared it with a linear regression model and a fuzzy regression model. The analysis of the results showed a more consistency between the proposed model and the linear regression model than the fuzzy regression model. However, the linear model presents some limitations that the proposed model overcomes.

6.5. Fuzzy logic

Fuzzy logic is a heuristic approach that generalizes the standard logic, in which all statements are described by a binary code. Thus, fuzzy logic includes zero and one as extreme cases of truth and it considers the various intermediate degreed of truth. It is a technique for representing and manipulating uncertain information. Fuzzy logic is composed by a fuzzy rule base, fuzzification, fuzzy inference engine and a defuzzification interface. The rule base contains the set of rules and the IF–THEN conditions provided by the experts. In other words, the input data are fuzzified in the fuzzy inference layer by using as fuzzy rule base the IF–THEN scheme. Then, the fuzzification transforms the input values into fuzzy linguistic variables (Ma, 2020). Those are the fuzzy rules of a fuzzy logic. The inference engine determines the matching degree of the input with each rule, and it decides which rules can be fired. At the end, as suggest by the name, defuzzification is the opposite of the fuzzification which translates the linguistic values into a numerical value (Kayacan and Khanesar, 2016).

Fuzzy logic has been widely used in the past in the ship collision field (Hwang, 2002; Kao et al., 2007; Qu et al., 2011; Zaman et al., 2014; Bukhari et al., 2013). However, there is not a standard method to set the exacted fuzzy rules and that may create complications during the construction of the fuzzy logic (Işik, 1991).

In order to overcome this limit, Li et al. (2018) combined an adaptive fuzzy system with an ANN to calculate an indicator called the Collision Risk Index (CRI). The combination of two methods allows to perform complex logic operations and to realize self-learning of fuzzy systems. An adaptive fuzzy logic can modify the characteristics of fuzzy rules analogously to back-propagation neural networks (Cox, 1993). The back-propagation algorithm contains two phases: the forward and backward phases. In the forward phase, the output values and the local derivatives at various nodes are computed. In the backward phase, the products of these local values over all paths from the node to the output are accumulated (Aggarwal, 2018). The authors compared the results of an ANN with the results of the adaptive fuzzy neural network. DCPA and TCPA are used to calculate CRI and this was used as target. As input data they used: speed, heading, angle and distance of selected ships. Results showed that the prediction error of CRI of the ANN is 0.07, whereas the prediction error of the adaptive fuzzy neural network is 0.003. That means the prediction accuracy of the proposed model is higher than that of ANN.

Fuzzy logic can be also applied to assess risk in real-time. A fuzzy inference system was built for ship-bridge collision alert by Wu et al. (2019). A fuzzy inference system is a system that uses a fuzzy set theory to map inputs to outputs (Wang, 2001). The input data of the input layer were the distance from the bridge, heading of the ship, ship and wind speed, sea state, visibility and day-time/night-time. These data derived from AIS data and from domain knowledge. Fig. 6 shows the scheme of the fuzzy logic used by the authors, which is composed by an input layer, a fuzzy inference layer and an output layer. The fuzzy inference layer used the IF–THEN scheme and The collision risk is obtained after the defuzzification with center of gravity method. Also, the authors used a Min–Max method as fuzzy inference engine. Wu et al. (2019) applied the proposed model in a real scenario that occurred in Wuhan Yangtze River Bridge in 2018 and the risk of collision is calculated for various points of the ship's trajectory.

From historical data it is possible to see that the ship safely passed the bridge. However, the results show that the value of collision risk near the bridge is 0.50. That means the probability of ship-bridge collision is very high due to the fact the maneuverings of the ship are not perfect.

Another application of the fuzzy inference system was done by Namgung et al. (2019), which combined it with an ANN to establish the ship CRI. Analogously to Li et al. (2018), the combination of two methods allows to self-learn the fuzzy systems by taking into account ship dynamic parameters, such as distance between ships or their velocity. They calculated the DCPA and TCPA to deduct CRI and they introduced an ANN to optimize the fuzzy inference system. The authors used AIS data of Mokpo sea area (South Korea) as input vectors (e.g. ship speed, distance, ship courses). The whole dataset was divided in three parts: 70% was selected for the training phase, 15% for the validation phase

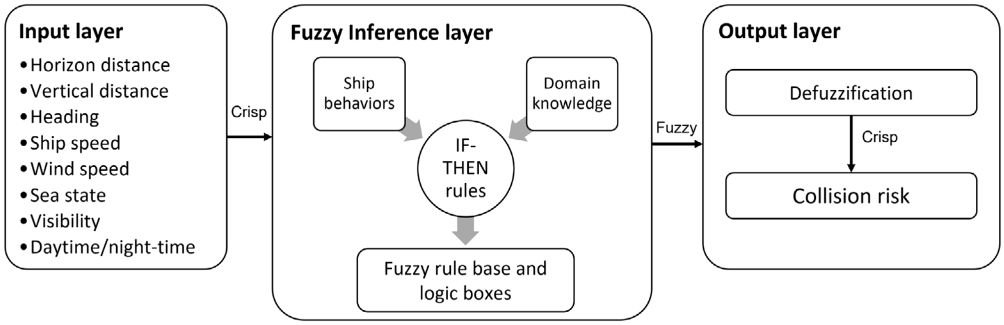

Fig. 6. Schematization of the fuzzy logic-based collision risk model (after Wu et al. (2019)).

and 15% for the test phase. The models gave different results of CRI, however the ANN presented better performance. Indeed, the data fitting was good as average R values (0.90).

A fuzzy logic is also used in the Hu and Park (2020)'s work, which combined it with an AHP in order to consider "vulnerabilities". With this term, the authors mean the probability that a marine accident can occur due to bad weather, strong tidal currents or operator fatigue. In particular, they calculated the DCPA and TCPA to use as input in a fuzzy logic. Also, six vulnerabilities are found by a team of experts and they calculated their values with the fuzzy logic. In addition, they applied AHP method to evaluate the integration of the vulnerabilities. The experts compared the importance of vulnerabilities (criteria), two at time, giving a number from 1 to 9 and an importance matrix of vulnerability factors is built. The analysis of results showed that when the traffic and environmental influences are not considered into the collision risk analysis, the predictive model fails to recognize the collision scenario. In particular, when a vulnerability increases, the probability of ship collision increases as well.

Similar results were found by Hu et al. (2020), which focused on fishing vessels collision risk using a Fuzzy C-means algorithm. The latter one is a clustering method which permits to data to belong to one or more clusters. In particular, using one-day-AIS data of Mokpo area (South Korea), firstly, the authors calculated the DCPA and TCPA in order to obtain the basic collision risk through a fuzzy logic; then, they used the dynamic information of AIS data to divide into clusters the ships. Also, the authors take into account the vulnerability (Hu and Park, 2020) considering the distance and the size of fishing area. Combining the basic collision risk and the vulnerability using a fuzzy logic, the collision risk is found.

More recently, Aydin et al. (2021) proposed a Fuzzy Bayesian Networks (FBN) to evaluate the ship collision risk. The fuzzy logic allows to treat the uncertainty and the vagueness of the BN. They applied the model in a real ship collision scenario that occurred on July 2017 at the English Channel. A heterogeneous group of experts evaluated the ship collision probability and weights are applied on their evaluations based on their professional qualifications, experiences and educational levels. The authors used a trapezoidal and triangular membership functions during the fuzzification and the center of area approach as defuzzification method. They found that the most important influent factors for the ship collisions were human error, management and organization errors. In addition, a FTA was built to validate the results obtained by FBN.

6.6. Human factors analysis and classification system

According to Fan et al. (2018) 80% of the ship traffic accidents are determined by personnel, including both human errors and logistics/organizational system failures. The Human Factors Analysis and Classification System (HFACS) is a widely used accident analysis tool to determine human and organizational factors in system failures. In HFACS, human error is not considered the cause of the accident, but rather the symptom of a larger safety problem. Within an organized system, four barriers are established to prevent events that could eventually cause the accident: organizational influences, unsafe supervision, preconditions for unsafe acts and unsafe acts. Four levels of barriers are established to avoid the accident. Within each level, failures determine holes, which correspond to a failure in the barrier. Failures can either be active or latent, with the former occurring right before the accident, and the latter being a systematic inadequacy of the safety system. When an accident occur, at least one failure is happening at each barrier, meaning that preventing at least one failure would eventually avoid the accident. This is called the Swiss-cheese model (Wiegmann, 2000), schematized within the HFACS framework in Fig. 7. Efforts to assess maritime risk with HFACS were conducted in the last decade (Batalden and Sydnes, 2014; Akhtar and Utne, 2014; Mazaheri et al., 2015). These works were already recently reviewed by Yıldırım et al. (2019).

In the same work, Yıldırım et al. (2019) proposed a novel method to study the maritime collisions and grounding accidents using HFACS and statistical methods. They analyzed 68 collisions and 189 grounding accidents occurred between 1991 and 2014 and, also, the different accident causes were divided into categories. To implement the HFACS structure, both data obtained from official reports or accident reports and experts' judgements were used. Then, the causes of collision accidents found by a group of experts were 194 and the most frequent categories were decision errors, resource management, violations, communication errors, adverse mental state, inadequate work planning and incompetence. For grounding scenarios, the experts found more causes than collision scenarios. More in details, the most frequent categories were resource management, decision errors, violations, physical environment, adverse mental state, incompetence and technological environment. The authors also compared HFACS categories using Chi Square Test and they found that unsafe acts and preconditions are the most important causes both in collision and grounding accidents.

Qiao et al. (2020) proposed a novel model, called MAMAC (Multidimensional Analysis Model of Accident Causes), based on HFACS and on FBN to analyze the human errors during a maritime accident. In particular, accidents report that occurred in China in 2018 and experts' judgements are used as input data and then the model is tested for a real maritime accident scenario. First the authors analyzed accident reports and determined risk factors. Then, the experts investigated the human factors behind of these accidents and they continued to explore until all the potential human factors are identified. The authors identified 54 human errors. To develop the FBN, a trapezoidal membership functions is used as a fuzzification method and the center of area approach is used during the defuzzification.

6.7. Fault-tree analysis

FTA is a deductive analysis method which allows, by means of graphical/logical framework, to link together the failures of the components of a system. The main purpose is not to identify the causes of

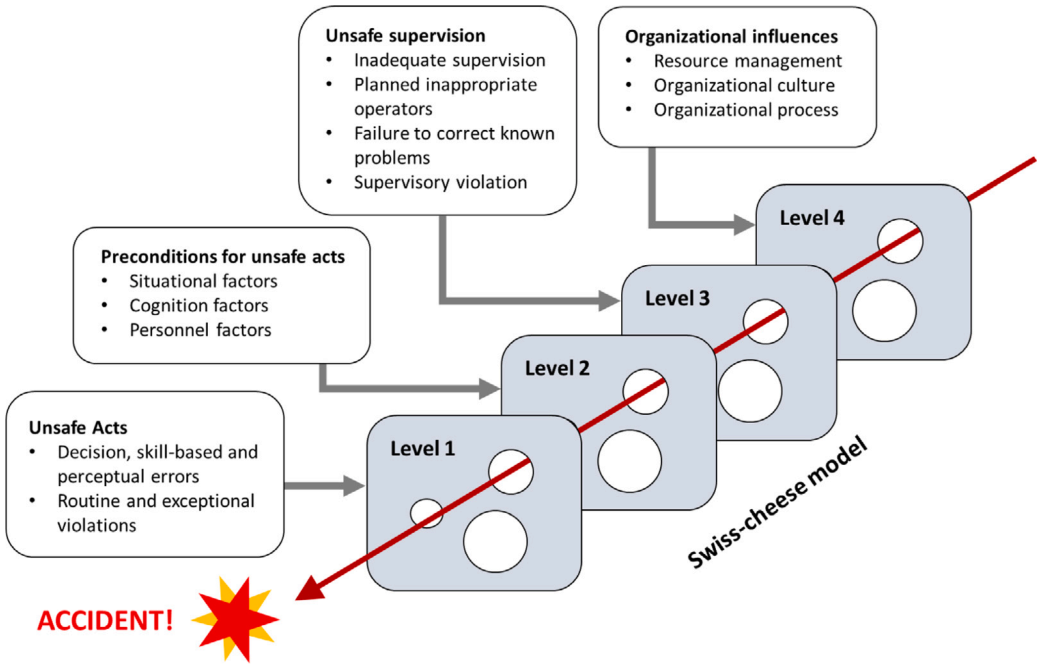

Fig. 7. HFACS framework.

faults but, starting from a failure of the system (Undesirable Event), to establish a functional relationship with the faults on the components (Basic events). FTA has various applications and can be used both preventively as well as to identify already detected causes of non-compliance. Specifically, it consists of the construction and in the analysis of the fault tree, composed by a critical event, called top event, connected to a series of blocks representing events which, linked to appropriate logic gates, determine the probability of occurrence. The top event identifies the failure of the entire system with the consequent emergence of problems from the point of view of safety. The FTA starts from an unwanted event and moves backwards in search of the causes that triggered it, indeed to build the fault tree is necessary to identify the top event first and after that the causes of the fault. Then, a simplification of the tree can be done, reducing it through the rules of Boolean algebra and obtaining an equivalent tree of Minimal Cut Set. The probability of occurrence of the Top event is analytically calculated starting from the probability that the basic events will occur.

Thanks to its simplicity to implement, FTA has obtained popularity in maritime risk assessment (Antão and Guedes Soares, 2006; Martins and Maturana, 2010; Yao et al., 2010; Chen et al., 2015; Uğurlu et al., 2015). However, FTA is a binary system due to its inability to consider the partial failures. Moreover, in a large system, i.e. when multiple factors are considered, the construction of FTA may become complicated due to its need to consider many gates and events (Fussell, 1975). FTA is also considered as a static technique due to its inability to update the probability.

To improve such disadvantages of the FTA, Arici et al. (2020) applied a fuzzy bow-tie analysis to quantify the collision risk between ships during the ship-to-ship operations. The bow-tie method combines the FTA and the Event Tree Analysis (ETA) in order to obtain a logical relationship between the causes and the consequences of an event. ETA is a logical model that main purpose is to identify and quantify the possible consequences of an initiating event. In other words, a FTA can have many initiating events all leading to the same top event; whereas, an ETA has only one initiating event which can lead to several consequences. In this study, the authors used this method under a fuzzy logic environment in order to deal with the imprecision of experts' judgements. More in detail, the FTA diagram is built and the Top Event of the diagram is the collision risk. For each basic event the experts gave their judgements, a fuzzy logic is used to convert linguistic terms in fuzzy numbers. Then, in order to quantify the collision risk, a value of 0.23 was calculated for the probability of occurrence of the Top Event and it confirms that the collision accidents play an important role in the ship-to-ship operations. Also, the ETA diagram is built as well, and the probabilities of the consequences are calculated. The authors categorized a set of human factors failure causes and found that the main causes of the collision accidents are “not to follow the maneuvering plan”, “lack of appropriate monitoring at close quarters” and “not to check the condition of mooring roper and tails”. Also, from the ET analysis, six consequences were found and the “near miss” one is the main consequence that can occur after a collision accident.

Another approach was proposed by Sakar et al. (2021). They combined a FTA and a BN to analyze the risks of grounding accidents from 2005 to 2020 in European waters. In particular, the FTA is used to identify the main root causes and then, it is converted into a BN to evaluate the consequences of the roots. Input data were collected from accident databases such as MAIB, IMO-GISIS (IMO-Global Integrated Shipping Information System) and European Maritime Safety Agency. The factors that caused grounding are 34 and the probability calculated with the FTA and with the BN is the same. Also, the BN updates its probabilities introducing the probability of basic events calculated using the FTA. At the end, the authors conducted a sensitivity analysis to evaluate the model.

A similar approach was developed by Sokukcu and Sakar (2022). They decided to combine a FTA and a FBN in order to avoid collision during berthing maneuvers. Taking into account marine experts' opinions, the FTA is built to find the basic events related to the top event (collision) and for each basic event, fuzzy logic is applied in order to evaluate the failure probability. Similar to the study of Sakar et al. (2021), the FTA was also converted into a BN to evaluate the probabilistic relationship between the causes of collision accidents. The results of the model showed that the root nodes: ‘mooring line breakdown’, ‘main engine failure’, ‘steering system failure’, ‘inadequate planning’, ‘poor communication’ and ‘commercial pressure’ had the greatest influence on collision accidents.

More recently, Ugurlu and Cicek (2022) used the FTA to study ship collisions accidents that occurred since 1977 in all international waters. The data were collected from different databases such as National institution (e.g. MAIB) or Global marine accident databases (e.g. GISIS). The Top Event of the FTA is ship collision and it is caused by human related failures or other failures such as design errors or mechanical failures. A quantitative analysis showed that most of the accidents are related to human errors. The probability of occurrence of the Top Event is calculated and results showed that the probability value related to human failures is higher than the one related to other failures; that means the majority of ships collisions is caused by human errors. In addition, Multiple Correspondence Analysis (MCA) is conducted to study the relationship between primary causes and their inertia and to develop prevention strategies. In particular, MCA is a data analysis that consent to visualize a data table containing more than two categorical variables. For this study, primary causes are studied in two dimensions, and the MCA determined that maneuvering and perception errors are the most effective factors in collision accidents.

6.8. Density-based clustering methods for multiple ship encounters

Modeling multiple ship collision scenarios is a particularly relevant matter for Vessel Traffic Systems (VTS), and maritime control centers in general, to manage ship traffic and warn navigators from potential encounters. In this case, the computed risk is associated to an area rather than to a single ship, and it is called regional collision risk. The use of multi-ship encounter modeling is necessary for unmanned and intelligent ships navigation management, and more in general can improve the efficiency of VTS systems by reducing cognitive load on VTS officers (Xinping et al., 2021).

To identify risk areas, clustering techniques can be employed. Clustering is an unsupervised machine learning method that subdivides a dataset into clusters, consisting of similar data points. Among clustering methods, Density-Based Spatial Clustering of applications with Noise (DBSCAN) methods identify and separates clusters high-density areas from low-density ones (Ester et al., 1996). In comparison with other clustering methods, DBSCAN has better performance with sparse or noisy datasets. DBSCAN outperforms other clustering techniques, such as k-means or hierarchical clustering, which are more suitable for well-separated data clusters, generally performing poorly in the presence of outliers and sparse data.

The use of DBSCAN in maritime ship collision is very recent. An example of its application is the one of Liu et al. (2020), which combined DBSCAN, Shapley value method (Cano-Berlanga et al., 2019) and a RNN using AIS data as input. In particular, the collision risk is calculated for each vessel cluster, grouped by the DBSCAN, using the DCPA and TCPA as risk indicators. The Shapley value method, which is a solution concept used in cooperative game theory, is applied to determine the summing weight of clusters. Then, the RNN is built. The input data included the previous input information and the current ones, and those connections are saved in the hidden layer. The input used by the authors consisted in the AIS data and the collision risk value and the output is the forecasting of the collision risk.

Another application of DBSCAN using AIS data is the one by Chen et al. (2021). For each ship group, they calculated the time-varying collision risk (TCR). TCR considers that the states of ships, and consequently the probability of collision, are time varying (Huang and van Gelder, 2020). In this context, TCR-based risk analysis permits to identify the potential collisions between ships in real-time and quantify the risk for each ship. Potential collisions were identified using Velocity Obstacle (VO) method (Fiorini and Shiller, 1998). VO was developed to study the motion of robots in dynamic environments, where obstacles are represented in the velocity space and avoidance maneuvers are generated in order to avoid collisions. Similarly, in this study, the velocity space of the ships and their movements are considered. Then, VO represents the collision velocities of a ship with another one moving at a given velocity. Knowing VO and the potential collisions, it is possible to quantify the risk using three indicators: critical-distance TCR, quaternion ship domain and encounter complexity. In particular, the first one is based on the critical distance of ship; the second one depends on ships' domains and the last one on the influence of ships' navigation.

Zhen et al. (2022a) studied the multi-ship collision risk using an arena-based assessment method, a DBSCAN and synthetic indicators (e.g. DCPA and TCPA). DBSCAN was applied to AIS data of ship off the coast of Sweden, where the encounter distance of ships is the neighborhood radius of DBSCAN and noise points are the safe non-encounter ships. Two risk models were studied: in the first one DCPA and TCPA were calculated and a mathematical relation between them and the collision risk is identified, whereas the second one is based on Arena model. The latter one is a domain based on the distance between crews and the target ship when it starts to take action to avoid an urgent situation (Davis et al., 1980). Comparing these two models, it is possible to notice that the second one is more robust and more efficient to identify ships with high collision risk.

A similar study was conducted by the same authors for the Xiamen Bay in China (Zhen et al., 2022b). They applied the DBSCAN using AIS data as input. In this study, they take into account the aggregation density of the clusters, which reflect the influences of the other ships around the Own Ship. Also, analogously to their previous study (Zhen et al., 2022a), DCPA and TCPA were calculated and the collision risk was identified for each cluster. After that, the authors displayed the whole spatial distribution of regional collision risk in a map on the nautical chart, which could a helpful tool in the traffic and risk management.

From the same authors, the effectiveness of another approach to study multi-ship collision risk was investigated. Ziqiang et al. (2022) proposed a fuzzy inference method including the ship crossing angle and the navigational environment in order to obtain a complete picture of the factors that may cause the collisions. In particular, AIS data of ships in Taiwan Strait were collected and divided into clusters through the application of the DBSCAN and for each cluster, DCPA and TCPA were calculated. Fuzzy logic is used to quantify those factors and the risk weight is calculated through the AHP to obtain the overall collision risk of the ship. As they did in their other work (Zhen et al., 2022b), the authors displayed the risk in a heat map.

6.9. Swarm intelligence algorithms

Longhorn beetles have two long antennas. These antennas are provided with receptor cells, making them able to sense odours to find preys or mates. When one of the antennas senses a higher concentration of odour, the beetle moves in that direction. To mimic such behavior, Jiang and Li (2017) developed the Beetle Antenna Search algorithm (BAS). The algorithm follows 5 steps (Fig. 8): (i) movement initialization, (ii) randomization of antenna movement, (iii) calculation of the fitness value of the two antennas, i.e., estimation of value right- and left- side movements (iv) update of the beetle centroid, i.e. the beetle moves in the best direction found in the previous step, (v) update of the current optimal position.

BAS falls in the wider category of Swarm Intelligence algorithms, i.e. algorithms inspired by the collective behavior of a decentralized, self-organized system. These systems consist of numerous individuals with limited intelligence interacting with each other based on simple principles. In ship collision risk, some efforts have been done with these technologies, such as ant colony optimization (Lazarowska, 2015) and particle swarm optimization (Tsou and Hsueh, 2010). These are known not to be time-consuming even though the size of the population is large (Xie et al., 2019a).

Xie et al. (2019a) used the BAS algorithm, a model predictive control and a simplified hydrodynamic model to predict ships collision. They simplified Abkowitz hydrodynamic model (Zhang and Zou, 2011),

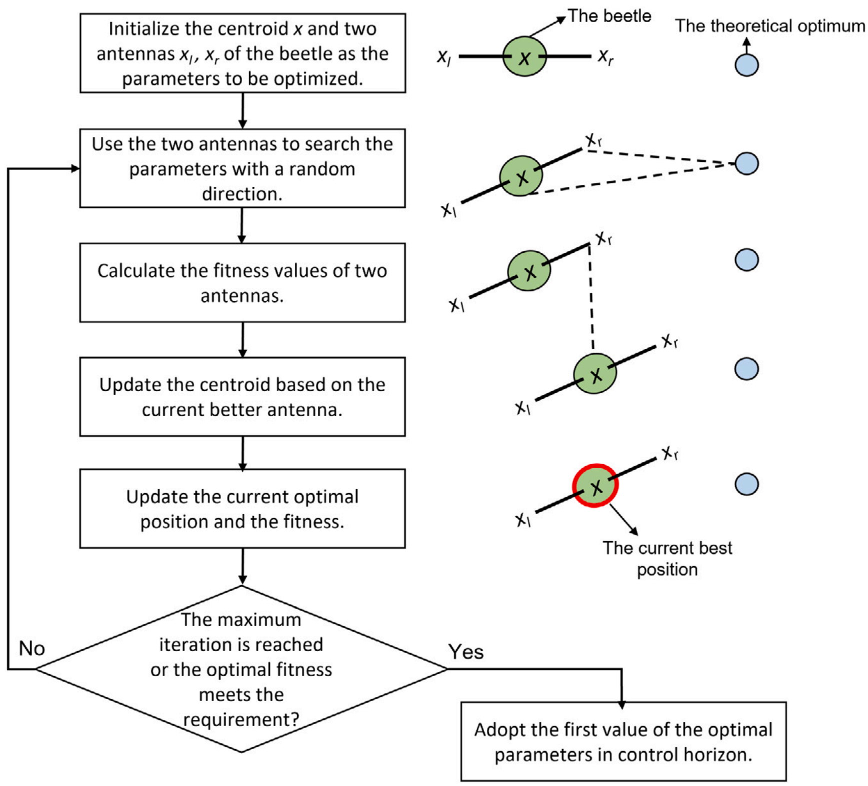

Fig. 8. Flowchart of the BAS algorithm (after Xie et al., 2019a).

in which the whole ship (including rudder and propeller) is considered, ignoring different higher order terms in Taylor expansions of the force and moment. The authors used a model predictive control based on DCPA and TCPA to establish the predictive ship collision avoidance strategy and as reported in Xie et al. (2019b), an improved BAS was used to overcome the optimization problem. In the original BAS algorithm, the antennae are related to the position of the centroid, and it is easy to fall into local extremum. In order to overcome this limit, the authors developed an improved BAS algorithm which performs better than the original one in terms of optimization and convergence times. Moreover, the authors simulated three collision scenarios: head-on, crossing and overtaking to validate this algorithm, reporting that the improved BAS obtained better collision avoidance results than the original one in all three scenarios.

Xie et al. (2019b) proposed a novel, time-efficient model to study the ship collision risk based on model predictive control (MPC), Q-learning beetle swarm antenna search (Q-BSAS) algorithm and an inverse neural network. MPC is a control algorithm which aim is to reach an optimum trajectory by manipulating the variables. In this study, it is used to establish the predictive ship collision avoidance strategy. However, MPC solves optimization problems on a finite prediction horizon and in order to overcome this limitation, the authors introduced a new algorithm based on Q-learning (Q-BSAS). They also trained a neural network to build an inverse model. The inverse model is formed by the inverse relationships between the input data (DCPA, TCPA) and the target (collision risk) and it is connected to the original system. The authors report that the Q-BSAS had a better performance than the BAS and the inverse model reduced the time cost.

6.10. Human error probability

A human error could be defined as the difference between the actual action and the one that should have been taken. They can be classified as unintended, e.g. lapses of memory or slips of action, and intended actions, e.g. deliberate violations and mistakes (Reason, 1990). As mentioned before, the large majority of maritime accidents are due to human error and their identification and quantification play an important role in risk assessment. The quantification of human error attempts to estimate how probable an error is to occur. According to Kirwan (2008), the ratio of errors committed to actual opportunities for errors to occur is known as the Human Error Probability (HEP):

$$\text{HEP} = \frac{\text{number of performed errors}}{\text{number of given opportunities for error to occur}} \tag{3}$$

Over the years, different approaches to estimate HEP have been developed. One of them is CREAM (Cognitive Reliability and Error Analysis Method) (Hollnagel, 1998). CREAM evaluates the probability of a human error occurring through the completion of a specific task. It allows to identify potential actions or task which may be affected by human cognition and to develop measures to reduce likelihood of errors occurring. CREAM uses the Contextual Control Model as a cognitive model, which is based on four basic control modes (observation, interpretation, planning and execution). It also uses a classification scheme, which consists of phenotypes (error modes) and genotypes (causes). The first ones describe how errors could potentially occur, whereas the genotypes describe the causes of the errors (Felice and Petrillo, 2018). A set of common performance conditions, such as working conditions, time of day, available time and crew collaboration quality are used to describe the context of the analyzed scenario.

In maritime collision risk assessment, CREAM is widely used to treat casual factors of human error (Mitomo et al., 2012; Yang et al., 2013; Ung, 2015; Wu et al., 2017; Xi et al., 2017). However, it may require high training and execution times. Also, it is built by using expert judgements and may be inherently influenced by subjective uncertainties. To overcome those limits, Ung (2019) combined a FBN with a fuzzy CREAM model in order to estimate the probability of an oil tanker collision in the Taiwanese Strait. The methodology takes into account the quantitative impacts brought on by the environment without the influences of experts' uncertainties. The expert opinions of 39 specialists helped to build the FBN in which the top event is collision and the basic events are related to human errors. Each basic event is evaluated using seven common performance conditions based on a fuzzy set and then HEP is calculated. Results showed that the collision probability is sensible to the variations of some basic events such as fatigue and interpretation failures, where heavy workload it the major cause of fatigue. Also, procedure violations present the higher value of HEP, which means they are the major cause of collision accidents.

Another method for calculating HEP is the DEMATEL model (DEcision MAking Trial and Evaluation Laboratory) (Fontela and Gabus, 1976). It is a widespread method that can assess and formulate every linked cause and effect relationship in structural models. It can be used to visualize the structure of complex causal relationships by using matrices or digraphs (Thakkar, 2021). Its construction consists in three main steps, which generate a direct-relation (average) matrix, a normalized direct influence matrix and a total-relation matrix. In particular, the average matrix consists in a pair-wise comparison of the influence between the decision factors; the normalized one represents the direct effects among factors and the total-relation matrix represents both direct and indirect effects (Falatoonitoosi et al., 2013).

Thanks to its ability to verify the interdependence among components of a system, DEMATEL is another widely used model in maritime risk assessment (Mentes et al., 2014, 2015; Özdemir and Güneroğu, 2015; Celik and Akyuz, 2016). A recent advancement in DEMATEL modeling was done by Ma et al. (2022). The authors proposed an integrated model composed by HFACS, DEMATEL model and Fuzzy Cognitive Map, aiming to identify and quantify the causation relationship of human error in a maritime accident scenario. Fuzzy Cognitive Map is a soft computing method based on cognitive maps that stores information in the connections between concepts and simulates the dynamic behavior of complex systems by analyzing how each concept in the network interacts with the others (Kosko, 1986). In particular, this new methodology contributes to solve the static and dynamic relationships between factors. HFACS was used to identify the human factors which contribute to marine accidents. DEMATEL model is applied to estimate the causality of the factors and to obtain an effect relation diagram. The Fuzzy Cognitive Map allows to model the dynamic relationship among factors by current state assessment and scenario simulation. From the analysis of the results, "not familiar with the Collision Regulations" has the highest value of influence over other factors and, consequently, on ship collision.

7. Discussion

The success behind traditional GIAs stems from their simplicity of application and low computational costs. Although there is room for future improvements, such as incorporating the effects of maneuverability, collision elasticity, and heavy traffic conditions, it is generally not feasible for GIAs to effectively model multi-encounter scenarios. They are indeed inherently limited by their conceptual framework which allows only to consider Target Ship-Own Ship relationships, making them unsuitable for simulating scenarios of multiple encounters.

In this regard, ANNs offer a promising alternative, thanks to their high predictive potential and their suitability to modeling complex, dynamic scenarios. In ship risk collision assessment, ANNs are generically trained using ship traffic images as input data, although large memory space and high learning time are generally required for the analysis and interpretation of the images. To this aim, reinforcement learning algorithms were recently introduced to improve the training performance, allowing the ANN to learn through trial and error procedures rather than requiring a large amount of training data.

One of the main limitations of ANNs is that they rely on precise numerical inputs and may struggle when handling ambiguous or uncertain data. This can be dealt with fuzzy mathematics. Thanks to its ability to transform quantitative inputs into fuzzy linguistic variables, it is able to handle complex and ambiguous inputs in a relatively simple way. However, fuzzy mathematics often involves subjective judgement and decision-making, such as assigning membership values to uncertain data or defining membership functions. This can introduce subjectivity into the analysis and make it more difficult to replicate or validate the results. Another area of potential improvement is in the flexibility and adaptability of ANNs. Currently, ANNs can be difficult to modify or update once they have been trained, which can limit their usefulness in dynamic environments. In this regard, techniques of modular neural networks, transfer learning or incremental learning could be implemented (Rosenfeld and Tsotsos, 2020).

In the case ANNs are unsuitable due to high learning time or need for flexibility, Bayesian Networks are an efficient alternative, being able to effectively reflect complex dependencies between variables, easily update their structure, integrate experts' knowledge and handle the uncertainties in a relatively simple way. Unlike ANNs, the structure of the BNs can be easily modified by adding additional influencing nodes without completely redesign the network, by just specifying their prior probabilities and parent nodes. BNs also offer the advantage of being able to incorporate variables difficult to quantify, such as situational awareness and mental workload. However, the large number of possible interactions between ships, particularly in complex scenarios involving multiple vessels, may generate ambiguous relationships between the nodes. In this sense, a possible future improvement could be the inclusion of automated disambiguation algorithms. They can be useful when it is not possible or practical to manually disambiguate an ambiguous node using expert knowledge or domain-specific knowledge. Machine learning algorithms can be trained on data from the network to identify patterns and relationships that can be used to disambiguate the node. Automated disambiguation approaches include the use of supervised learning algorithms to learn the structure of the network, unsupervised learning algorithms to identify patterns in the data, and reinforcement learning algorithms to learn the optimal way to modify the network structure.

One way to more easily integrate interdependent factors into a collision risk assessment model is to use a MCDA approach, which involves evaluating a range of factors and assigning weights to each factor based on their significance. MCDA is generally more suitable when multiple conflicting objectives are involved, however, as the number of variables increases, by including, for instance, weather conditions, maneuverability, logistics and human factors, it may be challenging to identify and weight all of the relevant criteria. Moreover, it may not be as effective at predicting the likelihood of different outcomes, as it does not take into account the probabilistic relationships between variables and rather relies on subjective weights assigned.

Clustering algorithms can be used to identify high risk multiple collision areas. In this sense, the DBSCAN results the most effective to deal with the scattered boundaries of traffic ship spatial distribution. The main issue with DBSCAN is that a set of parameters related to shape and size of the cluster needs to be specified in advance. Choosing appropriate values for these parameters can be challenging, especially for datasets with complex or non-uniformly distributed clusters. Moreover, DBSCAN is sensitive to the order in which the points are processed, which can affect the final results of the clustering. Another potential problem with DBSCAN is that it does not perform well on datasets with large numbers of noise points, causing the algorithm to identify many small, insignificant clusters. Moreover, DBSCAN is also not well suited to datasets with varying densities, which can cause the algorithm to identify clusters of very different sizes and shapes. A potential improvement in this regard is the development of methods for incorporating additional constraints or requirements into the clustering process. For instance, it may be possible to develop methods for incorporating constraints on the size or shape of the clusters, or for incorporating additional information about the relationships between the data points. DBSCAN is a purely objective algorithm, and the results of a DBSCAN analysis do not depend on the individual conducting the analysis. This can make DBSCAN more consistent and reproducible, but may also make it less flexible and adaptable to different situations and contexts.

HFACS provides a comprehensive and structured approach for analyzing and identifying the root causes of accidents. As it is fundamentally a subjective tool, the results of an HFACS analysis can vary depending on the individual conducting the analysis. This can be seen as both a disadvantage, as it may make it difficult to compare results across different studies, and an advantage, as it allows for flexibility and adaptability in the analysis process. HFACS is a widely used and well-established tool, with strong empirical foundations and a large body of research and case studies to support its use. This can provide confidence in the analysis results and can make it easier to compare and replicate the findings of different studies. A problem with using HFACS is that it is a complex system and may require significant training and expertise to use effectively. Another potential problem with using HFACS is that it is focused on identifying human factors as the root cause of accidents, which involves an intrinsic uncertainty.

HEP approaches provide structured frameworks for understanding and analyzing the factors that contribute to human error, which can help to identify opportunities for training and other interventions to reduce the occurrence of errors. There are potential areas of development and advancement in the field of HEP. As more data becomes available on human errors and their causes, it may be possible to use data analytics and machine learning techniques to identify patterns and trends, and develop more targeted and effective interventions to prevent errors. Additionally, there is growing interest in the use of cognitive engineering techniques, such as cognitive task analysis and cognitive workload assessment, to better understand the mental processes and constraints that influence human performance and to design systems and processes that support rather than hinder these processes.

The review revealed recent applications of beetle algorithms in ship collision risk assessments. Swarm intelligence algorithms can be used to simulate the behavior of large groups of ships in various scenarios, and then evaluate the effectiveness of different strategies for avoiding collisions in each scenario. As a step forward, swarm intelligence algorithms could be used to simulate the behavior of groups of ships and their crews, taking into account factors such as the individual skills and experience of the ship's captain and crew, as well as other human factors such as fatigue, stress, and workload. However, beetle algorithms may not be well suited to the complex, dynamic environment of shipping traffic when the number of variables increases. Beetle algorithms are designed to simulate the collective behavior of a group of simple agents. However, including human, logistics and organizational factors may be a challenging task. Additionally, beetle algorithms typically require a large number of agents to produce reliable results, which can be computationally intensive and may not be practical for real-time applications.

The reviewed methods were categorized according to recent classification systems in order to frame them in the current literature and identify their context of application. The review showed that the majority of available approaches classify as Strong Realists, with less than 30% of the considered methods falling into the Proceduralist or Constructivist categories. This trend confirms what has been observed by Ozturk and Cicek (2019), with a reported 70% of realist methodologies from 1995 to 2017. Qualitative methodologies remain the minority in the maritime collision risk assessment panorama to the present day. In order to cope with the scarcity of quantitative data, a possible solution could be using traffic conflicts (otherwise called *near-misses*) instead of actual collision datasets (Debnath et al., 2011). However, although such a framework would be preferable on an ethical basis as it does not act reactively to the occurrence of accidents, traffic conflicts are often not censused in many ports and waterways, or they are classified following very different distance or safe-boundary standards. On that note, data augmentation or synthetic data generation techniques could be an alternative to amplify scarce datasets (Shorten and Khoshgoftaar, 2019).

8. Conclusion

In the present paper, a review of the most recent technologies for ship collision risk assessment was presented. The review discussed new and emerging technologies as well as significant improvements on well-established methods, highlighting the main challenges, limits and opportunities. By presenting a detailed analysis of the most recent approaches and technologies used to assess collision risk, the review is intended to support safety authorities and industry investors to make informed decisions about how to best mitigate collision risk and to identify opportunities for future investments. At the same time, the review is also intended to be of interest to the safety science and engineering community. Risk analysis and management is crucial for maritime traffic systems to prevent occurrence of accidents and mitigate their consequences on individuals and society. The analysis presented in this work can provide valuable insights for risk assessors and safety scientists to better understand the technical value of current research methods.

List of acronyms

A3C	Asynchronous Advantage Actor–Critic
AHP	Analytical Hierarchy Process
AIS	Automatic Information System
ANN	Artificial Neural Network
BAS	Beetle Antennae Search
BN	Bayesian Network
C	Constructivist
CNN	Convolutional Neural Network
CoRI	Collision RIsk model
CPA	Closest-Point of Approach
CRI	Collision Risk Index
CREAM	Cognitive Reliability Error Analysis Method
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
DCPA	Distance to Closest-Point of Approach
DEMATEL	DEcision MAking Trial and Evaluation Laboratory
DNV	Det Norske Veritas
ELECTRE	Elimination Et Choix Traduisant la Realité
EMSA	European Maritime Safety Agency
ER	Evidential Reasoning
ES	Environmental Stress
ETA	Event Tree Analysis
FBN	Fuzzy Bayesian Networks
FSA	Formal Safety Assessment
FTA	Fault Tree Analysis
GIA	Geometric Indicators Approach
GISIS	Global Integrated Shipping Information System
GT	Grosse Tonnage
HEP	Human Error Probability
HFACS	Human Factors Analysis and Classification System
IMO	International Maritime Organization
ISPS	International Ship and Port facility Security
ISY PORT	Integrated SYstem for navigation risk mitigation in PORTs
LSTM	Long Short-Term Memory
MAIB	Marine Accident Investigation Branch
MAMAC	Multi-dimensional Analysis Model of Accident Causes
MARPOL	International Convention for the Prevention of Pollution from Ships
MC	Moderately Constructivist
MCA	Multiple Correspondence Analysis

MCDA	Multi-Criteria Decision Approach
MPC	Model Predictive Control
MR	Moderate Realist
MRU	Moderate Realist with Uncertainty assessment
PC	Precautionary Constructivist
Q-BAS	Q-learning Beetle Swarm Antenna Search
QSD	Quaternion Ship Domain
RCMs	Risk Control Measures
RCOs	Risk Control Options
RIFs	Risk Influencing Factors
RNN	Recurrent Neural Network
SAA	Statistical Analysis Approach
SBA	Safe Boundary Approach
SC	Strong Constructivist
SCR	Spatial Collision Risk
SI	Synthetic Indicators
SOLAS	Convention on the safety Of Life At Sea
SP	Scientific Proceduralist
SR	Strong Realist
SVM	Support Vector Machine
TCPA	Time to Closest-Point of Approach
TCR	Time-varying Collision Risk
VA	Velocity-based approach
VO	Velocity Obstacle
VTS	Vessel Traffic Systems

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

The data is available through a Mendeley Data repository (DOI: http://dx.doi.org/10.17632/rwwfg3r5yc.2)

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