Assessing ship collision risks in maritime transport based on seafarers' experience

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Abstract:

Assessing ship collision risks considering human factors presents persistent challenges due to the multivariate uncertainties faced by seafarers. Therefore, this study proposes a fuzzy-logic-based method to model ship collision risks in an area considering human factors. This method utilizes a hierarchical fuzzy system consisting of two fuzzy systems, fuzzy system 1 and fuzzy system 2, which are used to calculate the temporary risks and human factors, respectively. Aggregating the risks from both subsystems produces the overall collision risk index. This approach streamlines on-board risk appraisal, thereby reducing the navigator workload. While the current study delineates the risk modeling methodology, succeeding works validate the framework through simulated experiments. With adequate verification, this hierarchical fuzzy approach can assist next-generation risk-regulated navigation practices and enrich maritime agencies' traffic risk management.

Keywords: Maritime collision risk; Fuzzy logic; Human factor; Traffic density; AIS data.

1. Introduction

Unlike other transportation modes (road and air transport), maritime transport is a unique form of transportation characterized by complex and unpredictable safety risks originating from different stakeholders in the maritime industry. Moreover, maritime accidents can become disasters due to tremendous difficulties in rescue operations, such as the catastrophic oil spill of the crude oil tanker EXXON Valdez in Alaska in 1989. Although new regulations and guidelines are continuously introduced by the International Maritime Organization (IMO) and maritime safety agencies to improve maritime transport safety and prevent maritime accidents, such accidents remain a major issue facing the maritime industry, and maritime safety has yet to be improved to an optimal level. Injury or loss of life at sea, significant damage to or loss of cargo, and marine pollution are some common consequences of maritime accidents [1]. To prevent maritime traffic accidents, proactive measures coupled with advanced operational technologies and modern management methods proposed by stakeholders have become a widely discussed topic. However, many areas still need to be researched to ensure top-quality maritime transport, and maritime accident investigation is regarded as an effective approach to prevent maritime accidents.

Of all the causes of maritime accidents, human error, including both human error and organizational error, is considered the major cause. In the 2000s, the impact of human error on maritime accidents was approximately 80%, leading to increased research in this area [2], [3]. In fact, as early as the 1970s, the importance of the human element in maritime accidents has been internationally recognized, spurring the development of the famous International Convention on Standards of Training, Certification, and Watchkeeping for Seafarers (STCW convention), providing a detailed framework to improve and enhance seafarer competency. However, the human element in maritime accidents has been widely characterized by high uncertainty owing to diverse technical and operational issues. The importance of the human element in maritime operations is continuously referred to by international organizations such as the International Maritime Organization (IMO), the International Labor Organization, and the International Association of Classification Societies. Hence, this issue is receiving considerable attention and concern from other researchers to minimize or constrain the influence of human elements in maritime accidents by introducing proactive solutions.

The main contribution of this article is the proposal of a regional ship collision risk modeling method based on fuzzy logic, considering the impact of human factors. This method can be used for quantitative maritime risk assessment of ships, thereby enhancing safety in the maritime field.

This study is structured into four main sections. Section 1 is the introduction, presenting the rationale for choosing the research topic, as discussed above. Section 2 reviews related studies, specifically the essential parameters and methods of risk determination carried out previously. Section 3 proposes a human factor-incorporated risk modeling methodology. The final section discusses the directions for future research.

2. Literature review

To minimize the likelihood of ship collisions, many researchers have conducted extensive research on ship collision risks from various perspectives and methods, achieving certain research results. The author divided the research area content into two parts: Important parameters in risk determination and applied methods.

2.1. Parameters in ship's collision risk determination

Throughout the research process, many parameters related to ship collision surveys were identified and are listed below.

The commonly used parameters are the ship design characteristics relevant to the collision situation, such as the ship length and beam [4]. Ship navigational features such as speed, position, and angle of approach [5], [6] are three crucial parameters under consideration, along with Distance at Closest Point of Approach (DCPA) and Time to Closest Point of Approach (TCPA). This is understandable as the two parameters DCPA and TCPA show great dependence on the three parameters mentioned above. Sea state [7] and working conditions such as time of day, weather, and ship atmosphere [8] are other important parameters appearing in ship collision research papers.

The parameterization of the human element, although very complex, is indispensable. Notably, according to other statistics, human error accounts for 75-96% of maritime casualties that have occurred [9]. The officer on watch (OOW) is fundamentally involved in managing the collision situation (detection, action, avoidance), and thus the whole process revolves around them, with many human, equipment, and interaction factors affecting human performance. Some of the above factors are internal and external communication and organizational and human perceptual factors. The experience and skills of OOW are factors that shape their ability to perceive and judge risk. The adequacy of equipment (steering system) and positioning systems (ECDIS, Paper charts, Radar, GPS), along with human interaction with them, is also very significant. Quantifying these factors is an important issue. However, the connection of parameters with human factors, and especially with OOW performance, makes the quantification process an extremely difficult task.

2.2. Methodologies used in determining ship collisions

Many methodologies are being considered and developed in the scientific community to study ship collisions and assess their risk levels.

One of the most common methods is Fault Tree Analysis (FTA), which is the development of a physical system into a structured logical diagram [10] and related events are related to each other by cause and effect [11]. Martins and Maturana [12] performed a human error contribution analysis for the case of collision and/or grounding of an oil tanker on the Brazilian coastline using FTA to estimate the probability of causing a collision event. Similarly, in the study by Uğurlu et al. [13], the calculation of collision probability was performed based on various factors.

Additionally, some researchers have investigated human factors related to maritime accidents. Er and Celik qualitatively analyzed the role of the human element in a maritime safety management system [14]. Subsequently, a model based on human reliability assessment was developed for maritime accidents in Greece [15]. However, evaluating human factors related to maritime accidents is difficult owing to the lack of human factor data in the maritime industry. Thus, various other assessment techniques developed by scholars and safety practitioners can be used to analyze human risk factors related to maritime accidents. These techniques can be divided into two branches: empirical and expert techniques. Empirical techniques emphasize collecting data on human factors and evaluating human factors based on databases of human reliability. Moreover, human factors related to worldwide ship accidents occurring during 2000 – 2012 were collected and investigated by Eliopoulou et al. [16] and Goerlandt [17] collected and investigated maritime accidents occurring in the Northern Baltic Sea in 2007 and 2013. Expert judgment is gaining increasing attention due to the complexity and uncertainty of human factors related to maritime accidents. One increasingly prominent method is fuzzy set theory. This theory is considered to be the reasoning method closest to human perceptual ability. In the context of maritime safety, fuzzy set theory provides a powerful tool to capture and handle uncertainty, enabling better decisions in risk management and accident mitigation. With the capability of risk assessment through uncertain data owing to the dynamic nature of the marine environment and humans [18], simulation of human decision-making in complex and ambiguous situations [19], it has also been used to improve some methods such as fault trees to assess risk based on human judgment instead of hard data, and other integrated models applying fuzzy logic have also been applied. In situations lacking quantitative data, fuzzy logic allows the use of expert knowledge and experience for risk assessment.

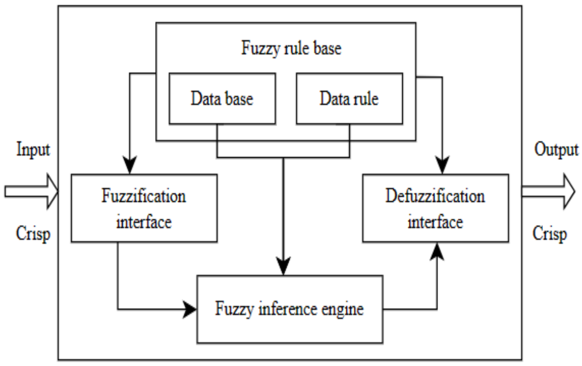

Figure 1. Generalized fuzzy inference system.

Therefore, this paper presents a regional ship collision risk method based on Fuzzy Logic. Fuzzy logic uses membership functions to process input relationships and simulate the human brain to perform rule-based reasoning (if...then). Fuzzy logic can simulate the human brain to perform rule-based reasoning, which is modeled to automatically and continuously warn about ship collision risks. This study utilizes the fuzzy logic method, which has significant advantages in quantifying ship collision risks under various operating conditions.

3. Proposed ship collision risk assessment base on fuzzy logic

3.1. Fuzzy inference model for risk determination

Fuzzy logic is a widely used method for risk analysis in maritime transport. This method uses degrees of truth as a vague mathematical model and uses linguistic variables to represent input factors, which is especially useful for collision risk assessment because this field is influenced by many factors, and the evaluation of one factor is often uncertain, inaccurate, or vague [20]. Moreover, the defuzzified results from the linguistic variables are described by crisp values. This is intuitive for decision makers to take countermeasures to minimize ship collision risks.

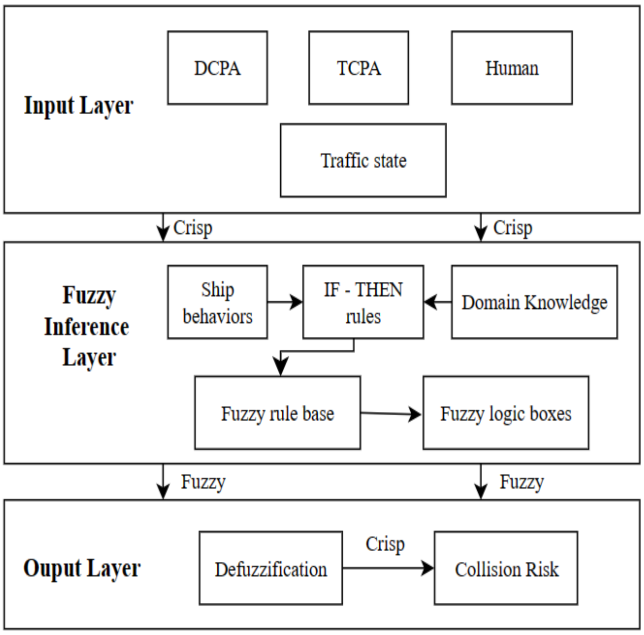

Figure 2. Collision risk model based on fuzzy logic.

As shown in Figure 1, the fuzzy inference system (FIS) consists of fuzzification, a fuzzy rule base, a fuzzy inference engine, and defuzzification. The process of FIS is as follows: Step 1: Crisp inputs are converted into fuzzy inputs using fuzzification methods. Step 2: The fuzzy rule base is constructed using fuzzy IF–THEN rules. Step 3: The fuzzy inference engine performs rule-based reasoning operations. Step 4: Defuzzification transforms the fuzzy reasoning results into crisp outputs.

By introducing FIS, a three-layer framework, consisting of an input layer, fuzzy inference layer, and output layer, was developed to assess ship-ship collision risk. The developed framework is shown in Figure 2, and the detailed description of the three layers is as follows. Note that when developing an FIS to assess collision risk, there are several FIS modules, which will be described in detail in a later section of this paper.

3.2. Calculation of FIS input parameters

3.2.1. Calculation of distance at closest point of approach (DCPA) and time to closest point of approach (TCPA)

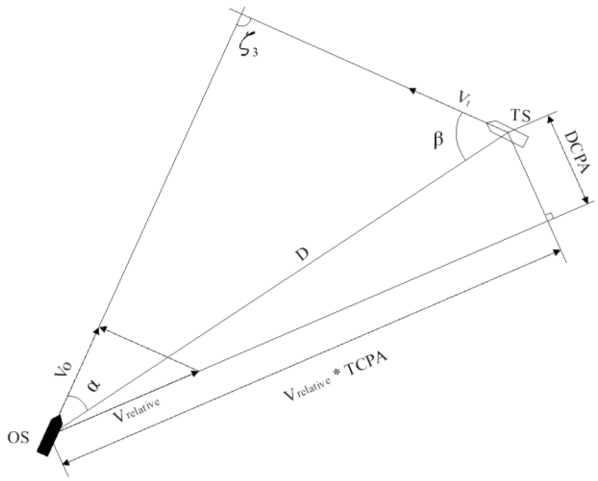

Figure 3. DCPA and TCPA in an approach situation between two ships.

In this section, the calculation of 2 input parameters for the Fuzzy module namely TCPA and DCPA is performed continuously in real time. The way to determine DCPA and TCPA can be described by Figure 2, where V_o is the speed of the own ship, V_t is the speed of the target ship, D is the distance from the own ship to the target ship, α is the relative angle of the target ship with respect to the own ship and β is the relative angle of the own ship with respect to the target ship.

In the study of Dinh and IM Namkyun (2016) [21] it has been proven and used the following formula:

$$DCPA = \frac{D(V_o \sin\alpha - V_t \sin\beta)}{\sqrt{V_o^2 + V_t^2 + 2V_oV_t\cos(\alpha+\beta)}} \quad (1)$$

$$TCPA = \frac{D(V_o \cos\alpha - V_t \cos\beta)}{V_o^2 + V_t^2 + 2V_oV_t\cos(\alpha+\beta)} \quad (2)$$

The calculated results of DCPA and TCPA will be input to calculate the Temporary Collision Risk (TCR).

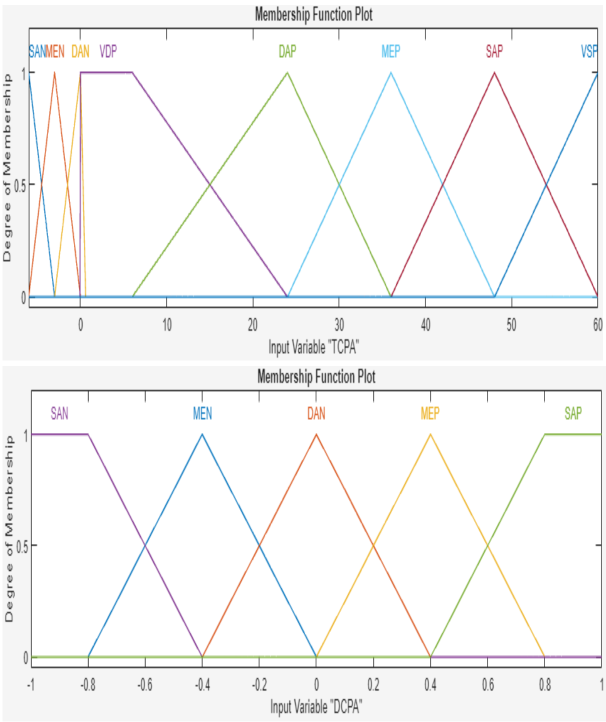

Figure 4. Membership functions of DCPA and TCPA.

The fuzzy system used here is adopted from the study of Dinh and IM Namkyun (2017) [22] as shown in Figure 4.

Where:

SA: Safe;

ME: Medium;

DA: Dangerous;

VD: Very Dangerous;

DA: Dangerous.

The letters N, P afterward indicate Negative and Positive values. In rule-based fuzzy systems, the relationships between the variables are expressed by fuzzy rules in the form:

If DCPA is at SAN and TCPA is at SAN then CR is at SAN

If DCPA is at SAP and TCPA is at VSP then CR is at VSP…

Combining linguistic functions using formula (3):

$$\mu(x,y) = \mathrm{I}(\mu_A(x), \mu_B(y)) = \min(\mu_A(x), \mu_B(y)) \quad (3)$$

Defuzzification using centroid formula (4) is as follows:

$$TCR = cog(C) = \frac{\sum_{j=1}^{F} \mu_C(cr_j)\, cr_j}{\sum_{j=1}^{F} \mu_C(cr_j)} \quad (4)$$

Which:

TCR: Temporary collision risk (crisp value) output value after defuzzification;

μ_C: Membership function;

cr_j: Value of the linguistic variable.

Thus, the Center of Gravity (COG) defuzzification method is used to calculate the TCR through the fuzzy system.

3.2.2. Determining human factors to assess collision risk (CR)

The human element in this study refers to the experience of OOW. The collision avoidance process is a process that depends heavily on factors and mainly on the experience and judgment of the OOW, as well as the complexity of the situation because there is no specific rule governing the optimal use of collision avoidance other than the COLREG convention combined with the traditional conventions of the seafaring profession.

In this study, the identified human factors consist of the experience of the officer on the watch and the degree of complexity of the situation that the OOW has to handle. The OOW's experience is determined by the time at sea under the officer's title:

With the advent of modern information technology, obtaining operating experience data of ship officers has become less arduous owing to the extensive digitization of crew member records across many countries over the past years.

The linguistic input variables representing the operating experience of Officers On Watch (OOW) are constructed based on their tenure of working at sea under officer designations. Specifically, OOW experience levels of 3 years, 4.5 years, and 6 years are linguistically termed as “low”, “medium”, and “high”, respectively (universal set U = [3,6]). The fuzzy quantification of these lexical terms is defined through triangular and trapezoidal membership functions, as illustrated in Figure 5 - “low” = (0, 0, 3, 4.5), “medium” = (3, 4.5, 6), “high” = (4.5, 6, 6, 6).

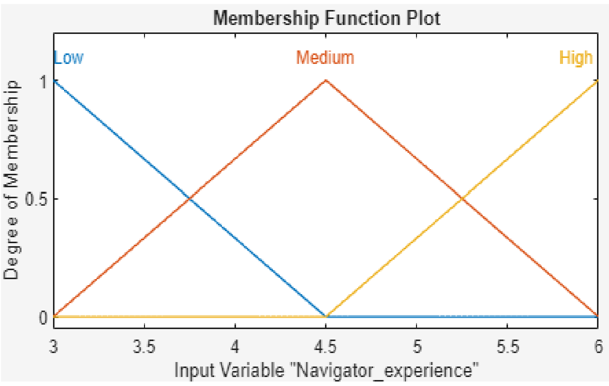

Figure 5. OOW's experience member functions.

The risk of collision escalates with high traffic density, while sparse areas exhibit lower collision hazards. The linguistic input variable “traffic density” is defined by three, six, and nine vessels in proximity that correspond to the qualitative ratings “sparse”, “medium”, and “dense”, respectively (universal set U = [3,9]). The fuzzy quantifiers representing these lexical terms are constructed through triangular and trapezoidal membership functions, as depicted in Figure 6 - “sparse” = (0, 0, 3, 6), “medium” = (3, 6, 9), “dense” = (6, 9, 9, 9).

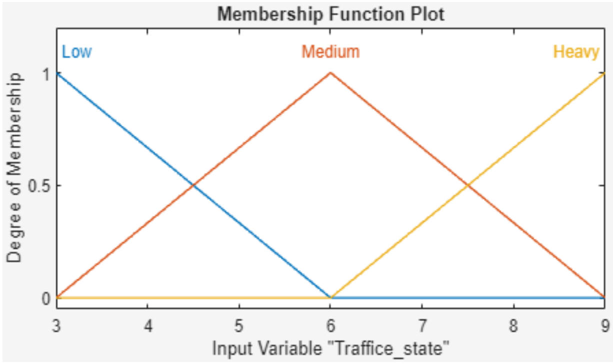

Figure 6. Traffic density member functions.

3.3. Establishing fuzzy rules to determine ship collision risk

Prior to constructing fuzzy rules, the input and output variables need to be defined. Due to the multitude of factors considered in this study, a sizeable fuzzy rule base would be formed, posing challenges in establishment and calibration.

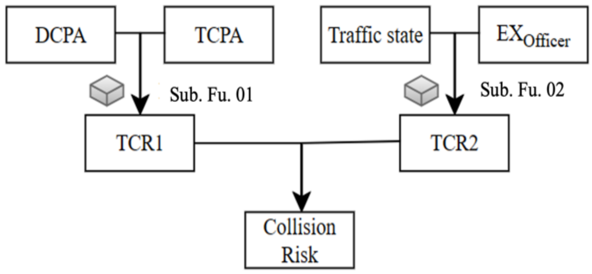

Figure 7. Hierarchical fuzzy system for collision risk assessment.

Hence, this paper proposes a hierarchical fuzzy modeling approach to assess ship collision risk by developing an aggregated-type two-layer hierarchical fuzzy system, as depicted in Figure 7. The lower-level comprises Level 1 with two fuzzy sub-systems that encompass factors related to the vessel density and the officer's experience, while Level 2 represents the output variable, collision risk index. With hierarchical architecture, the complex modeling task can be decomposed into more manageable and interpretable subtasks, mitigating the curse of dimensionality in conventional fuzzy rule-based systems.

Sub-fuzzy system 1 is constructed with time to closest point of approach (TCPA) and distance to closest point of approach (DCPA) as inputs, forming temporary collision risk 1 (TCR1) as output. Sub-fuzzy system 2 combines the linguistic variables of officer experience and traffic density to determine temporary collision risk 2 (TCR2). By feeding TCR1 and TCR2 as inputs into the upper fuzzy level, the final collision risk (CR) can be obtained.

The merits of this hierarchical approach are the simplification of the fuzzy rule-based formulation for each isolated subsystem and an easier tuning process. In addition, the aggregation of multiple relevant input information leads to more accurate predictions.

Table 1. Fuzzy inference rules for TCPA and DCPA.

Fuzzy linguistic values of DCPA	**Fuzzy linguistic values of TCPA**							
	SAN	**MEN**	**DAN**	**VDP**	**DAP**	**MEP**	**SAP**	**VSP**
SAN	SAN	SAN	SAN	SAP	SAP	VSP	VSP	VSP
MEN	SAN	MEN	DAN	DAP	MEP	SAP	VSP	VSP
DAN	SAN	MEN	DAN	VDP	DAP	MEP	SAP	VSP
MEP	SAN	MEN	DAN	DAP	MEP	SAP	VSP	VSP
SAP	SAN	SAN	SAN	SAP	SAP	VSP	VSP	VSP

Table 2. Fuzzy rules for traffic density and officer experience.

Fuzzy linguistic values of experience of officer	**Fuzzy linguistic values of traffic state**		
	Low	**Medium**	**Heavy**
Low	L	L	M
Medium	L	M	H
High	M	H	H

The fuzzy rule base constitutes the core of the fuzzy reasoning system, correlating all factors to derive the outcome. Fuzzy rules hold an IF-THEN structure; for instance, IF (DCPA is VS) and (TCPA is VS) THEN (spatio-temporal risk is DAN). Several sample rules are provided in Tables 1 and 2. The fuzzy rule formulation follows this convention; for example, if (DCPA is VS) and (TCPA is VS), then (the spatio-temporal risk is DAN). Some of the rules are presented in Tables 1 and 2.

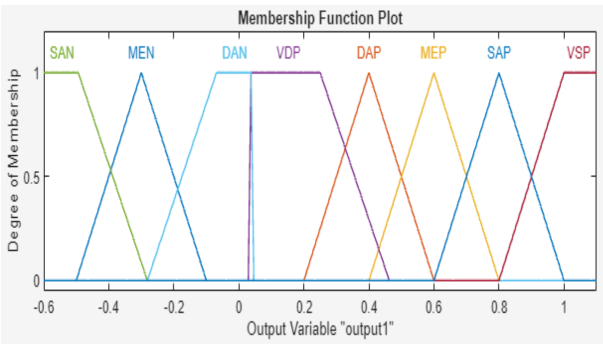

Figure 8. Membership functions for TCR1.

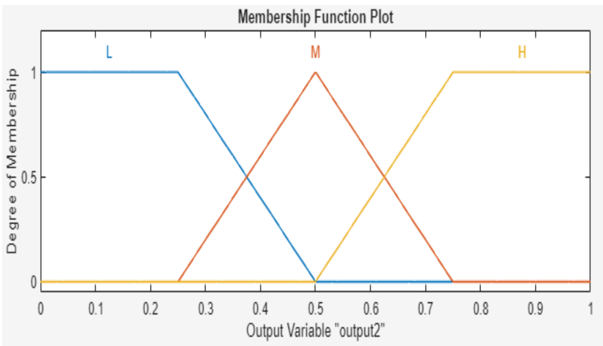

Figure 9. Membership functions for TCR2.

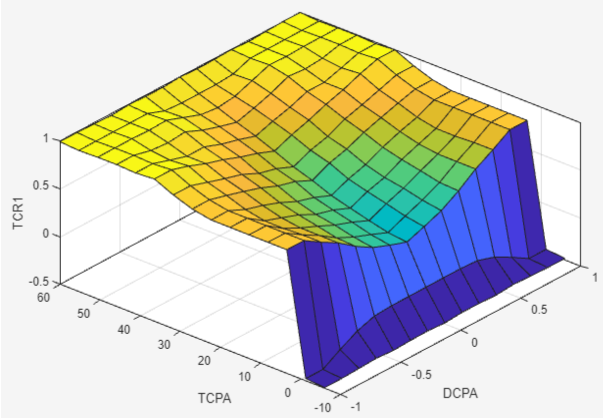

Figure 10. Rules of temporary collision risk 1.

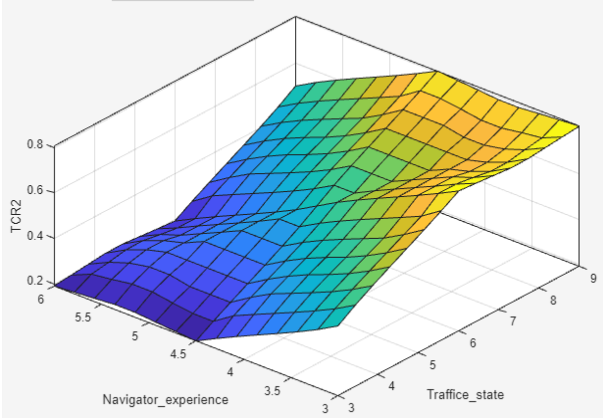

Figure 11. Rules of temporary collision risk 2.

Table 3. Fuzzy inference rules for ship collision risk.

Fuzzy linguistic values of TCR2	Fuzzy linguistic values of TCR1						
	SAN	**MEN**	**DAN**	**VDP**	**MEP**	**SAP**	**VSP**
Low	SAN	SAN	MEN	VDP	MEP	SAP	VSP
Medium	SAN	MEN	DAN	VDP	MEP	SAP	VSP
High	MEN	DAN	DAN	VDP	VDP	MEP	MEP

The method selected for defuzzification is the centroid formula in equation (4).

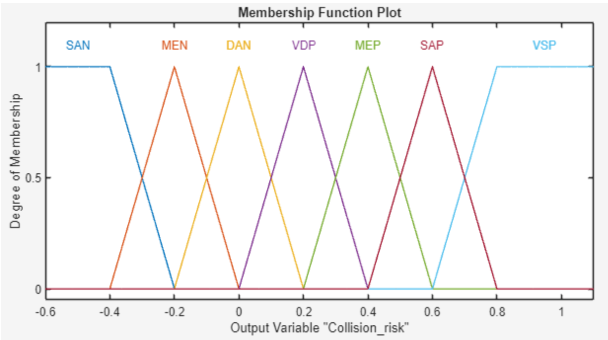

Figure 12. Membership functions for collision risk.

Thus, the research team established a model to assess the risk of ship collisions during maritime transportation. The use of a Hierarchical Fuzzy System yields more granular expected risk assessments of collisions, especially by accounting for mariner experience. The system can automatically compute the risk of collisions for surrounding ships, supporting the early issuance of necessary collision avoidance advice to officers of the watch, maritime traffic managers, and relevant parties.

4. Conclusion

This paper proposed a novel method based on fuzzy logic theory to model and assess the collision risk between vessels in a specific area. The approach employs a hierarchical fuzzy system comprising two sub-systems, in which the first sub-system calculates the temporary collision risk from the TCPA and DCPA parameters, while the second incorporates the OOW's experience and local traffic density for the final collision risk assessment. The merits of this technique are the ability to translate expert knowledge and maritime experience into computational collision risk rules, coupled with a human element to enhance predictive accuracy. The findings can provide scientific foundations for maritime traffic control and management in high-density waters.

In subsequent studies, the proposed model will be validated using empirical data and simulation test cases to further refine its robustness and reliability.

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