Maritime Ship Collision Risk Assessment Using Fuzzy Analytic Hierarchy Process Based on AIS Data

I Made Dwi Putra Asana, I Made Oka Widyantara, Linawati, Dewa Made Wiharta, and Ni Kadek Bumi Krismentari

Abstract—**The high density of maritime traffic is significantly increasing collision risk. This shows the need for more advanced and precise methods to assess collision risk. Therefore, this study aimed to introduce Fuzzy Analytic Hierarchy Process (F-AHP) to enhance the calculation of Collision Risk Index (CRI) using data derived from Automatic Identification System (AIS). Although conventional AHP effectively applied parameter weights, it often encountered limitations in scenarios where there are parameter conflicts, leading to less precise risk classifications. These limitations could be overcome by the proposed F-AHP, which integrated fuzzy logic by refining key parameters such as Distance to Closest Point of Approach (DCPA), Time to Closest Point of Approach (TCPA), and relative distance (Dr), to improve sensitivity in CRI calculation. To validate the effectiveness of F-AHP, a comparative analysis with AHP was conducted across multiple ship encounters, demonstrating that F-AHP provides more adaptive and context-aware CRI values. The results showed that F-AHP consistently identified higher-risk situations earlier than AHP, reducing underestimations in risk classification. Through discrete event simulation of ship movements, F-AHP showed stability and reliability in CRI assessment, ensuring proactive collision avoidance decisions. A statistical significance test ($t = 5.1315$, $p = 0.0068$) confirmed that F-AHP showed significantly different CRI values, suggesting its potential for integration into real-time ship traffic management systems (VTMS) and autonomous navigation platforms. These results showed the potential of F-AHP to enhance maritime safety through improved compliance with International Regulations for Preventing Collision at Sea (COLREGS) regulations and its applicability in real-time navigation systems.**

Index Terms— **AIS Data, Collision Risk Index, F-AHP, Maritime Safety**

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I. Introduction

SEA transportation is important in the global economy, particularly for maritime countries such as Indonesia with sea area of 3,544,743.9 km², significantly exceeding the land area [1]. The increasing maritime traffic, driven by the growth of international trade and the need for larger ships with great carrying capacity has caused a higher risk of ship collision. Moreover, collision, equipment failures, and fires, can cause significant losses including life, property damage, and environmental pollution [2], [3]. This shows the need for risk assessment of maritime collision is important to ensure the safety and security of shipping.

To mitigate risk of ship collision, International Maritime Organization (IMO) has implemented International Regulations for Preventing Collision at Sea (known as Collision Regulation/COLREGS) to provide guidelines on ship collision [4]. Additionally, Automatic Identification System (AIS) technology has been introduced as a navigation aid [5]. AIS data includes critical information such as a ship position, speed, course, and identity, enabling the tracking of behavior and the identification of potential collision [6]. One commonly used method for collision risk assessment is Collision Risk Index (CRI), an expert-based tool for evaluating the potential for AIS data-based ship collision, with values ranging from 1 to 0 [7], [8]. CRI value is influenced by several factors including Distance of Close Point of Approach (DCPA), Time to Close Point of Approach (TCPA), distance from the target ship, relative bearing, and speed ratio [3], [4], [9]-[11]. The most important characteristic is the uncertainty caused by measurement error. Initially, CRI can be assessed by summing the weights of DCPA and TCPA, followed by risk of ship collision assessment through experienced practitioners at sea [13]. When CRI value exceeds a predetermined threshold value, risk of collision will occur.

Several studies have been conducted to assess risk of ship collision. According to Yingjun Hu et al, ship collision risk assessment can be carried out using fuzzy methods [9]. Abebe et al used the D-S theory [12], while Namgung et al applied the neural network method [7], and Analytic Hierarchy Process (AHP) was introduced by Nguyen, et al [10]. These methods have been applied for calculating and analyzing risk of collision between ships to facilitate decision-making.

Previous studies on CRI assessment have generally used deterministic or probabilistic methods that base risk assessment on numerical values of parameters such as DCPA, TCPA, and Dr. Although the methods are useful, their application is unable to handle uncertainty and ambiguity [12], [11] that arise when parameter values are at two different risk levels. This can lead to confusion in determining the appropriate course of action, whether to follow the higher or lower risk level [10], [11].

Based on the description, this study aimed to introduce Fuzzy Analytic Hierarchy Process (F-AHP) method, to measure the potential for collision between ships. F-AHP is a multi-criteria decision-making method, which can be used as a determination of risk level evaluation [14]. Additionally, fuzzy logic enables models to describe uncertain or fuzzy values, similar to human thinking in complex situations. Integrating F-AHP facilitates the weighting and comparison of criteria that are important in risk assessment. The contribution of this study is the reduction of uncertainty and ambiguity in decision-making regarding risk of ship-to-ship collision at sea. By implementing F-AHP, this study offers a more decisive and accurate method to assessing collision risk. This is particularly important due to the ambiguity that often arises when DCPA, TCPA, and Dr parameter values are at two different risk levels causing confusion in determining the appropriate course of action. F-AHP also enables a clearer and more definitive determination of risk levels, allowing seafarers to take more appropriate and early precautions in accordance with COLREGS. Therefore, this study addresses the limitations of conventional methods by improving the accuracy and relevance of CRI assessments, ensuring close correlation with real-world conditions.

II. Literature Review

Studies on the use of AIS data for ship collision prediction have been conducted. These include the investigation by Yuxin Zao et al. with the title of a real-time collision avoidance learning system for unmanned surface ship. The investigation discusses the detection of collision risk of unmanned ships (Unmanned Surface Vehicles) using the Evidential Reasoning (ER) method which provides efficiency in CRI assessment. The weight of CRI value is calculated using AHP method [11].

Sheng-Lo Kao et al. explored a fuzzy logic method for collision avoidance in ship traffic service. The study used fuzzy methods to improve the decision-making ability of Vessel Traffic System (VTS) operators. The decision was used as a ship collision avoidance warning system. Furthermore, a platform called Marine Geographic Information System (MGIS) was developed, which provided mapping and spatial analysis capabilities to calculate risk of collision between several ships [15].

Ling-zhi Sang et al. conducted a study titled "CPA Calculation Method Based on AIS Position Prediction," which developed a method to calculate Closest Point of Approach (CPA) using AIS data. The study incorporated parameters such as Speed Over Ground (SOG), Course Over Ground (COG), Course Over Ship (COS), and Rate of Turn (ROT) to create a predictive model of a ship's position. This model enhanced the accuracy of CPA calculations by generating a precise trajectory from AIS data. The proposed method enhanced navigation decisions, thereby minimizing unnecessary maneuvers, and offering timely alerts regarding irregular ship behavior [16].

Longhui Gang et al. with the title Estimation of ship collision risk index based on support vector machine (SVM) discussed the prediction of ship collision. The data used consisted of 50 groups collected from six predetermined situations. During the analysis, two methods were used, namely SVM to predict CRI and genetic algorithm (GA) to optimize the parameters of SVM. The results showed that the algorithm provided good performance for CRI estimation [3].

Mingyou Cai et al. with the title Collision Risk Analysis on ferry ships in Jiangsu Section of the Yangtze River based on AIS data discussed risk assessment of ferry ship collision during crossing activities. The study assessed risk of collision and its integration from each trip based on historical AIS data. Furthermore, the method applied was Collision Risk Index of Ferry (CRIF) using several parameters including DCPA, TCPA, distance, and relative speed. The results obtained were the acquisition of risk of ferry collision in real-time and the proposed method functioned optimally [8].

Jie Ma et al. applied a data-driven method for collision risk early warning in ship encounter situations using attention-BiLSTM. The study discussed the early warning of ship collision risk for sailing safety that allowed officers to react to emergencies and take avoidance actions first. In line with the study objective, AIS data were from the East China Sea from January to April 2019, while the performance of LSTM was compared to attention-Bi-LSTM as a capture of spatio-temporal behavior dependence and future risks. The results provided valuable insights into early warning of risk of ship collision. From the comparison, the attention-BiLSTM algorithm was superior in accuracy and stability [17].

Building upon previous investigations, this study aimed to introduce measuring CRI of potential collision using F-AHP method with several factors including DCPA, TCPA, ship speed, ship angle, and visibility situation based on AIS data. The results provided information to improve uncertainty and ambiguity in assessing CRI, making the use of F-AHP method more relevant to the actual situation.

III. Materials and Methods

AIS is a maritime communication technology that enables ships to continuously transmit and receive key navigational data. The data includes ship name, type, timestamp, speed, position, heading, and voyage details, which are essential for enhancing maritime security and navigational safety [18], [19]. AIS plays a fundamental role in ship monitoring and collision avoidance by providing real-time situational awareness to maritime authorities and other nearby ships.

Before application, AIS data passes through preprocessing, which includes decoding, cleaning, and eliminating erroneous or incomplete records to ensure accuracy. After the data is refined, essential collision risk parameters DCPA, TCPA, and relative distance (Dr) are computed. These parameters form the basis for determining ship encounter situations, which are classified according to

COLREGS.

To enhance the precision of collision risk assessments, F-AHP is applied to refine CRI values. This method resolves classification ambiguities and provides a more nuanced risk assessment by incorporating fuzzy logic into traditional AHP-based decision-making. The complete system workflow, including AIS data collection, preprocessing, parameter computation, encounter classification, and CRI assessment using F-AHP, is shown in Fig. 1. This structured method ensures that maritime risk assessments are both reliable and actionable, supporting real-time navigation decisions to mitigate potential collision at sea.

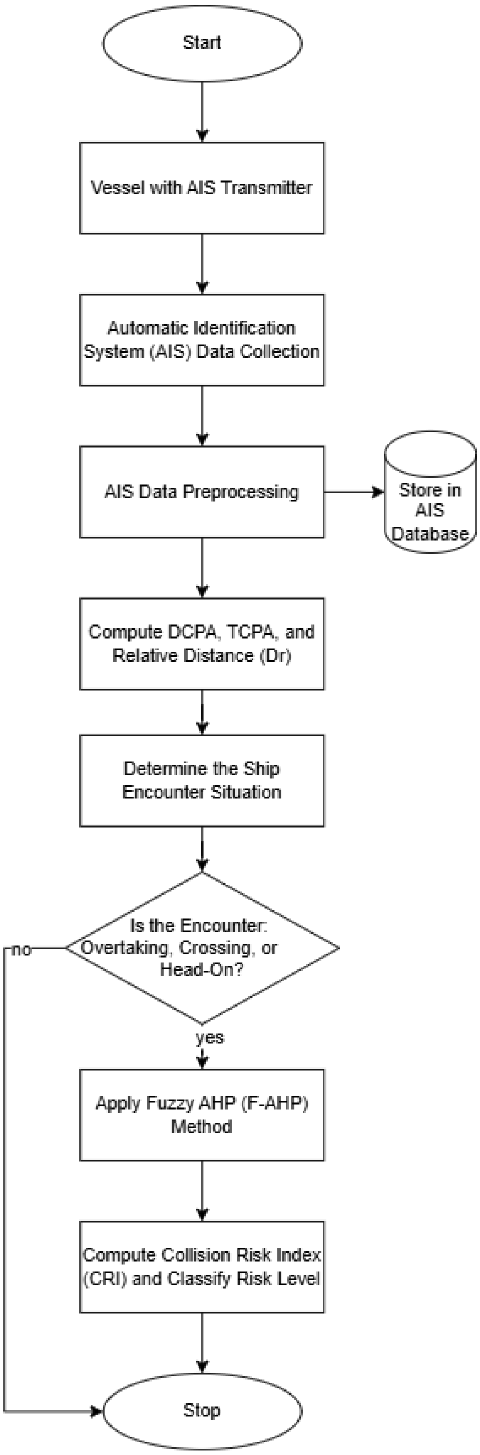


Fig. 1. System overview.

A. AIS Data Collection

Ship equipped with AIS devices generates a series of data containing information about the identity, position, and speed. In this study, AIS data used is a 2023 dataset covering ship activity in the waters of the Lombok Strait, Indonesia, captured from a terrestrial antenna installed at Udayana University.

B. AIS Data Preprocessing

AIS data had NMEA (National Maritime Electronic Association) format which requires decoding to obtain the real information contained in AIS message using the Python programming language. These data contain some information such as timestamp, type of mobile, MMSI, latitude, longitude, navigational status, ROT, SOG, COG, Heading, IMO, call sign, name, ship type, cargo type, width, length, type of position fixing device, draught, destination, ETA, data source type, A, B, C, and D [19]. AIS data are cleaned to remove unused data and improve quality. However, SOG value of 0 and COG outside 0-360 show the removal of stationary ship [20].

C. DCPA, TCPA, and Dr

For each nearby ship, parameter values are calculated to determine its position and assess the situation. The relative positions of two or more ships in close proximity indicate conditions where collision may become possible. The ship position will indicate the encounter point between Own Ship (OS) and Target Ship (TS). [21]. From the encounter conditions between OS and TS, the values of DCPA, TCPA, and Dr are derived. The information needed to calculate the parameter values is MMSI, Longitude, Latitude, Heading, SOG, and COG. Before obtaining the value of the three parameters, the bearing of each adjacent ship will be calculated by Equation (1):

$$\beta = tan^{-1}2(yOS - yTS, xOs - xTS) - \phi TS \tag{1}$$

Where β is bearing, x is latitude, y is longitude, ϕ is ship angle, OS represents Own Ship, and TS denotes Target Ship. In addition to bearings, the relative speed of the two ships is also calculated. The calculation of the relative speed is shown in Equation (2):

$$Vr = VOS \times \sqrt{1 + \left(\frac{VTS}{VOS}\right)^2 - \frac{VTS}{VOS} \times \cos(\phi OS - \phi TS)} \tag{2}$$

Where Vr is the relative velocity, and ϕr represents the relative angle. The relative angle provides information about how far one object is from another. The relative angle can be calculated using Equation (3):

$$\phi r = \cos^{-1} \times (\frac{VOS - VTS \times \cos(\phi OS - \phi TS)}{Vr} \tag{3}$$

Relative distance (Dr) is the distance between OS and TS based on time units [3]. The equation for calculating the Dr value is shown in Equation (4):

$$Dr = \sqrt{(xTS - xOS)^2 - (yTS - yOS)^2} \quad (4)$$

DCPA is the closest distance between two ships approaching each other, which is influenced by Dr, relative angle, and bearing of ship [3]. When DCPA is equal to 0, there is a tendency for collision to occur. Meanwhile, DCPA value> 0 shows a distance between one ship and another, with a tendency for risk of collision. The equation of DCPA is shown in Equation (5):

$$DCPA = Dr \times \sin(\phi r - \alpha t - \pi) \quad (5)$$

TCPA represents the time required for two ships to reach DCPA. Furthermore, it provides an estimate of when the two ships will be at their closest point to each other, maintaining current courses. When TCPA value is negative, it indicates that the closest point between the two ships has been passed and the ships are moving away from each other. However, a positive value suggests that two ships are approaching each other. When the TCPA value is less than or equal to zero, the two ships have crossed the threshold and collision will occur. Relative velocity (Vr) has a great influence on TCPA because, in Equation (6), TCPA is inversely proportional to Vr. In this case, Vr is the denominator, hence, the greater the value of Vr, the smaller the resulting TCPA value [16].

$$TCPA = Dr \times \cos(\phi r - \alpha t - \pi) / Vr \quad (6)$$

D. Determine Ship Encounter Situation

IMO issued the Convention on International Regulations for Preventing Collision at Sea 1972 which is often known as COLREGS 1972. This regulation is a resolution of IMO Number A. 464 (XII) that applies internationally and must be implemented in full by all ships, owners, skippers, and crew to avoid collision at sea [22]. The purpose of COLREGS is to provide instructions and rules to avoid collision between ships [23]. The five main rules of this regulation are *13*- overtaking, 14- head-on situation, 15- crossing situation, 16- action by give-way ship, and 17- action by stand-on ship. These rules are used to verify collision avoidance. [24]. Based on rules 13, 14, and 15, there are three ship encounter situations which are shown as follows [25]:

1) Head-on: When OS and TS meet on a head-on course including risk of collision, each ship must change course to starboard.
2) Crossing: When there is a ship from the starboard side, OS must give way. Crossing refers to two ships that encounter each other between 15◦ and 112.5◦.
3) Overtaking: OS will be considered overtaking when approaching TS from a direction >22.5 degrees behind ship. In this situation, OS will overtake from the port or starboard side of TS.

The classification of ship encounter situations is determined based on the relative course (ϕ) and bearing (α), which are computed from key navigational parameters obtained during AIS data preprocessing phase. These parameters include ship speed, COG, heading, and positional data (latitude and longitude), which are decoded and processed to derive precise encounter conditions, as shown in Table I.

TABLE I
SITUATION CONDITIONS OF SHIP ENCOUNTERS

Ship Encounter Situation	Conditions
Overtaking	$\phi \leq 25$
Head On	$165 \leq \phi \leq 195$
Crossing gives way to ship passing at the bow	$25 < \phi < 165$ or $195 < \phi < 335$ $\alpha \leq 90$ or $\alpha \geq 270$
Crossing gives way to ship passing at the stern	$25 < \phi < 165$ or $195 < \phi < 335$ $90 < \alpha < 270$

E. Fuzzy AHP

Fuzzy Inference System (FIS) is used to determine the output by mapping given inputs using fuzzy logic, which includes membership functions, fuzzy logic operators, and IF-THEN rules [26]. Fuzzy rules are formulated based on input values derived from ship movement parameters, ensuring a more adaptive and context-aware classification of collision risk. Table II shows the linguistic values assigned to the three key parameters, namely DCPA, TCPA, and Dr, which define CRI value [27].

To enhance the accuracy and adaptability of maritime collision risk assessments, this study implements F-AHP on the critical parameters. Compared to conventional AHP, which assigns rigid numerical thresholds to classify risk levels, F-AHP integrates fuzzy logic to smooth transitions between linguistic categories, reducing abrupt classification shifts that may misrepresent actual risk levels. This hybrid method refines uncertain parameter values, ensuring that ships with borderline DCPA, TCPA, or Dr values are classified more accurately rather than being forced into discrete categories. F-AHP implementation starts with the construction of a pairwise comparison matrix based on expert judgment, which determines the relative importance of DCPA, TCPA, and Dr. Subsequently, these parameters are converted into fuzzy membership functions, allowing for partial classifications across multiple risk categories.

TABLE II
LINGUISTIC VALUES OF PARAMETERS

DCPA	Value	TCPA	Value	Dr	Value
0-1,3	Collision	0-11,5	Collision	0-1,2	Collision
1,3-2,6	Danger	11,5-22,9	Danger	1,2-2,1	Danger
2,6-3,9	Threat	22,-34,4	Threat	2,1-3,0	Threat
3,9	Attention	34,4	Attention	3	Attention

The membership functions adopted in this study are based on the methodology presented in [27], which defines the input variable ranges for fuzzy evaluation as [0, 3.9] for DCPA, [0, 34.3] for TCPA, and [0, 3] for the relative distance (Dr). These ranges are carefully selected to represent the typical values encountered in maritime navigation scenarios and are instrumental in enabling fuzzy logic to capture degrees of risk more flexibly than conventional thresholding. The mathematical formulations of these membership functions, which are integral to the F-AHP-based CRI assessment, are presented in Equations (7) to (9) and used consistently throughout the decision-making framework.

$$\mu C\ DCPA = \begin{cases} 1, \ for\ DCPA \le 0 \\ \frac{1.3-DCPA}{1.3}, \ for\ 0 < DCPA \le 1.3 \end{cases}$$

$$\mu D\ DCPA = \begin{cases} \frac{DCPA-0}{1.3}, \ for\ 0 < DCPA \le 1.3 \\ \frac{2.6-DCPA}{1.3}, \ for\ 1.3 < DCPA \le 2.6 \end{cases}$$

$$\mu T\ DCPA = \begin{cases} \frac{DCPA-1.3}{1.3}, \ for\ 1.3 < DCPA \le 2.6 \\ \frac{3.9-DCPA}{1.3}, \ for\ 2.6 < DCPA \le 3.9 \end{cases} \tag{7}$$

$$\mu A\ DCPA = \begin{cases} \frac{DCPA-2.6}{1.3}, \ for\ 2.6 < DCPA \le 3.9 \\ 0, \ for\ 3.9 \le DCPA \end{cases}$$

$$\mu C\ TCPA = \begin{cases} 1, \ for\ TCPA \le 0 \\ \frac{11.5-TCPA}{11.5}, \ for\ 0 < TCPA \le 11.5 \end{cases}$$

$$\mu D\ TCPA = \begin{cases} \frac{TCPA-0}{11.5}, \ for\ 0 < TCPA \le 11.5 \\ \frac{22.9-TCPA}{11.4}, \ for\ 11.5 < TCPA \le 22.9 \end{cases}$$

$$\mu T\ TCPA = \begin{cases} \frac{TCPA-11.5}{11.4}, \ for\ 11.5 < TCPA \le 22.9 \\ \frac{34.3-TCPA}{11.4}, \ for\ 22.9 < TCPA \le 34.3 \end{cases} \tag{8}$$

$$\mu A\ TCPA = \begin{cases} \frac{TCPA-22.9}{11.4}, \ for\ 22.9 < TCPA \le 34.3 \\ 0, \ for\ 34.3 \le TCPA \end{cases}$$

$$\mu C\ Dr = \begin{cases} 1, \ for\ Dr \le 0 \\ \frac{1.2-TCPA}{1.2}, \ for\ 0 < Dr \le 1.2 \end{cases}$$

$$\mu D\ Dr = \begin{cases} \frac{Dr-0}{1.2}, \ for\ 0 < Dr \le 1.2 \\ \frac{2.1-Dr}{0.9}, \ for\ 1.2 < Dr \le 2.1 \end{cases}$$

$$\mu T\ Dr = \begin{cases} \frac{Dr-1.2}{0.9}, \ for\ 1.2 < Dr \le 2.1 \\ \frac{34.3-Dr}{11.4}, \ for\ 2.1 < Dr \le 3.0 \end{cases} \tag{9}$$

$$\mu A\ Dr = \begin{cases} \frac{Dr-2.1}{0.9}, \ for\ 2.1 < Dr \le 3.0 \\ 0, \ for\ 3.0 \le Dr \end{cases}$$

F. Calculation of CRI

CRI calculation is derived from the refined parameter values obtained through F-AHP, as shown in Section E. The implementation of F-AHP plays an essential role in refining DCPA, TCPA, and Dr, ensuring a more adaptive and sensitive risk assessment. By transforming these parameters into linguistic categories based on fuzzy membership functions, F-AHP mitigates abrupt misclassifications and ensures a smooth transition between risk levels. CRI formula, as defined in Equation (10), integrates defuzzified values of DCPA, TCPA, and Dr with their respective weight coefficients, showing the relative significance of each parameter in collision risk evaluation.

$$CRI = (a1\left(\frac{DCPA}{Ds}\right)^2 + a2\left(\frac{TCPA}{Ts}\right)^2 + a3\left(\frac{D}{Ds}\right)^2)^{-\frac{1}{2}} \tag{10}$$

In this context, Ds represents the minimum safe distance from the ship, while T_s refers to the time required to detect the risk of collision, formulate an avoidance strategy, and execute steering maneuvers. The variable D denotes the actual distance between the two vessels at any given moment. The parameters α_1, α_2, and α_3 serve as weight coefficients corresponding to each factor in the CRI equation, which collectively influence the severity of collision risk. These weights reflect the relative importance of variables such as environmental visibility, vessel dimensions (length and width), and the navigational characteristics of the waterway, including traffic density and maneuvering constraints. Adjusting these coefficients allows the model to adapt to varying maritime scenarios and reflect real-time conditions more accurately. Furthermore, the ability to assign differentiated weights enhances the model's flexibility in assessing risk under diverse conditions, such as restricted visibility or high-speed approaches. The collision level classification used in this study adheres to the COLREGS, as established in the study by [25]. The categorization of collision severity into distinct levels is detailed in Table III, which serves as a reference for interpreting risk thresholds.

TABLE III
COLLISION LEVEL

Level	Definition
Collision	The two ships collided
Danger	Both ships are required to take the most favorable action to help avoid collision.
Threat	Stand-on ship takes action to avoid collision. Give Way ships are required to take early and substantial action to achieve a safe distance to travel.
Attention	Stand on the ship must maintain ship angle and speed.

According to studies from [10] and [20], the criteria for calculating the Collision Risk Index (CRI) and issuing navigational warnings suggest that when the CRI value exceeds 0.667, the probability of an imminent collision is high. In such high-risk conditions, the vessel designated as the give-way ship must promptly execute avoidance maneuvers. These may include altering course, reducing speed, or implementing both actions simultaneously to establish a safer separation distance. Timely response is essential to avoid last-minute decisions that could increase navigational uncertainty. When the CRI falls within the range of 0.333 to 0.667, the potential for collision is considered moderate. While immediate evasive action may not be necessary, the ship giving way should maintain heightened vigilance and be prepared to respond appropriately if the situation deteriorates. Finally, when the CRI < 0.333, the encounter is classified as low-risk. The categorized levels of ship encounter conditions are visually represented in Fig. 2.

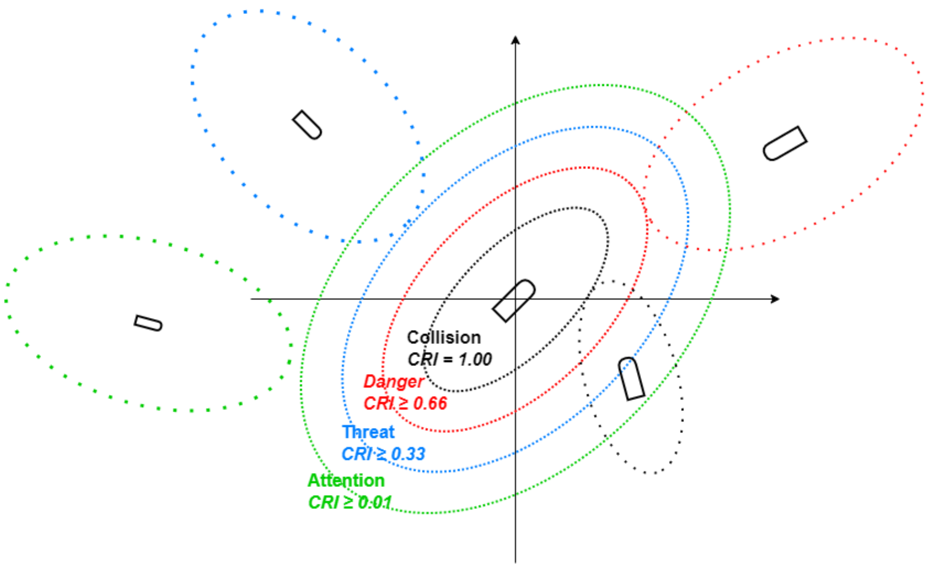


Fig. 2. The situation of ship encounters by level.

IV. Result and Discussion

AIS data used in this study are the 2023 dataset captured from terrestrial antennas installed at Udayana University. The data history has a CSV file format which is divided into daily files. The following is AIS data message which can be seen in Table IV.

TABLE IV
Historical AIS Data

Received	MMSI	Lat/Long	Heading	COG	SOG
02-02-2023 07.45	9130290	-8,659/115,4	268	268,7	22,8
	636018336	-8,362/115,8	199	199,2	12,7
	310499000	-8,901/115,6	190	184,9	13
	636021134	-8,828/115,6	192	188,3	9,8
	525401357	-8,681/116	283	283	9,8
	353321000	-8,653/115,8	16	16,8	12,8
	357203000	-8,408/115,8	199	198,6	12
01-02-2023 00.02	525010356	-8,437/115,8	323	319	10,3
	265829000	-8,928/115,6	201	199,6	12,9
	525401357	-8,559/115,5	108	104,9	10,2
	525008083	-8,573/115,6	72	77,7	8,9
	235108988	-8,873/115,6	199	195,2	9
	477087800	-8,6/115,8	21	19	9,6
	370968000	-8,881/115,6	201	194,7	9,4
02-02-2023 08.01	525301422	-8,14/116,0	269	276,9	7,2
	525119205	-8,075/117,1	266	268,5	7,7
	310499000	-8,96/115,6	188	183,1	13,4
	636018336	-8,415/115,8	200	199	12,4
	538005107	-8,189/115,8	200	196	11,5
	636021134	-8,872/115,6	192	187,2	10,1
	636017158	-8,738/115,7	17	14	13,2
	354707000	-7,971/116,0	22	25	11,3
	353321000	-8,601/115,8	17	18,3	12,2
02-02-2023 10.20	563119200	-8,060/115,9	208	206,5	12,7
	351772000	-8,046/115,9	202	201,8	10,7
	636018336	-8,824/115,6	195	192,7	10,4
	357203000	-8,840/115,6	195	193,3	10,1

In Table IV, there are several attributes including timestamp, MMSI, Latitude, Longitude, Heading, COG, and SOG. Timestamp is the time AIS signal is sent by the ship. Latitude and Longitude are the geographical locations of ship. The heading is the forward direction of ship in motion. COG is the direction of travel by ship at any given moment. Meanwhile, SOG is ship speed relative to other objects. Table IV is obtained from the results of the initial distance classification on the ship pair. In the calculation of CRI, the initial distance between pairs of ships is 6 nautical miles (nm) [3].

A. Near-Collision Ships Condition

In the domain of maritime collision risk assessment, the spatial closeness between vessels serves as a vital indicator for identifying potential collision situations. This study defines a near-collision scenario using a relative distance threshold of 6 nm. When two ships are detected within this range, the encounter is flagged for detailed analysis. This threshold acts as a trigger for further evaluation, prompting the calculation of essential collision risk parameters to assess the seriousness of the situation and support timely navigational decision-making.

The processed AIS data are mapped to visualize positions and detect near-collision conditions. This map enables the identification of ships that are in critical or close proximity to each other. To show and further analyze these situations, AIS data recorded on February 2, 2023, was examined, at 07:45, as presented in Table IV. A corresponding visualization of this encounter is shown in Fig. 3, representing ships that are near the threshold and forms the basis for further analysis.

According to Fig. 3, ships are plotted based on their relative positions. Black dots represent ships that are in the 6 nm threshold, indicating a near-collision condition. Meanwhile, red dots show ships that are still at a safe distance. This initial identification in Fig. 3 provides an essential context for narrowing down encounters that require closer examination, emphasizing specific ship pairs where collision risk parameters must be calculated in detail.

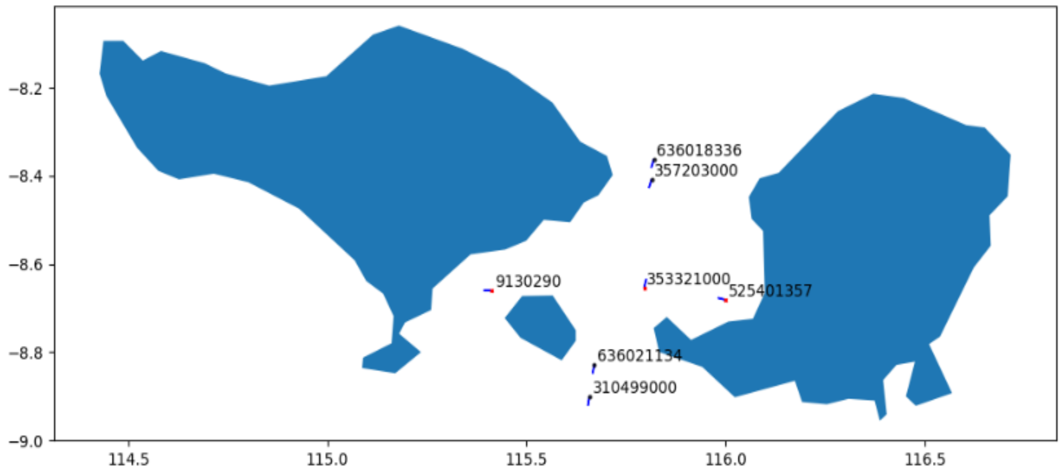
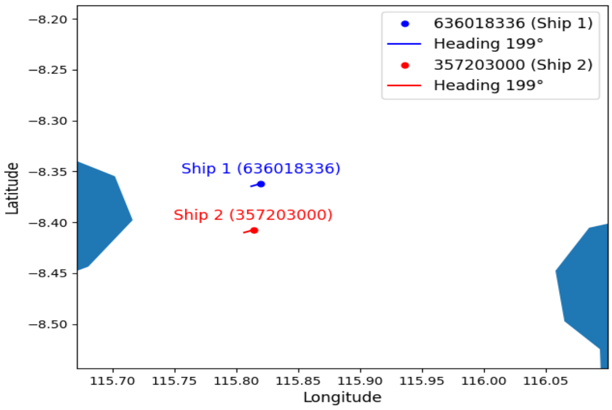
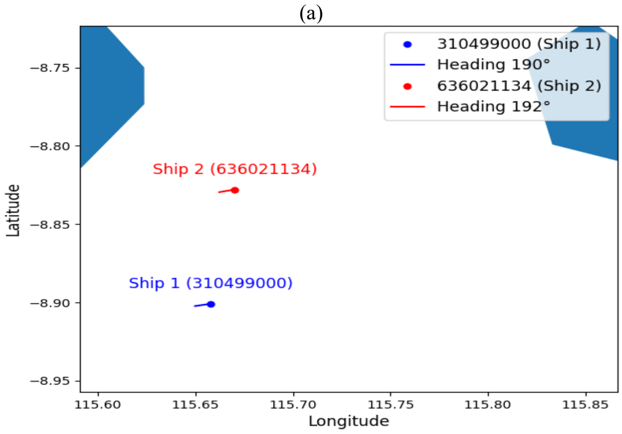


Fig. 3. Visualization of near collision condition.

Fig. 4 presents an in-depth visualization of two critical ship encounters initially identified in Fig. 3 as near-collision cases. These encounters, designated as Ship Pair 1 and Ship Pair 2, were flagged based on their relative distance in a 6 nm threshold, requiring further analysis to assess collision risk. The examination of these encounters includes calculating essential risk indicators, such as DCPA, TCPA, and Dr, with the results shown in Table V.



(a)



(b)

Fig. 4. Detailed visualization of ship position: (a) Encounter 1; (b) Encounter 2.

For Ship Pair 1 (MMSI 636018336 and 357203000), shown in Fig. 4(a), ship positions are in the 6 nm threshold, indicating a near-collision scenario. According to calculations in Table V, DCPA for the encounter is approximately 0.59 nm, categorizing it in Collision risk level due to ship close proximity. This low DCPA value suggests a high risk, requiring careful monitoring and possibly preemptive measures. TCPA is -0.35 minutes, indicating that ships have already passed their closest approach point and are now moving away. However, the low DCPA value shows that ships are recently at a critical proximity. Dr is calculated as 2.75 nm, determined based on ship latitude and longitude positions on Earth's curved surface, confirming the seriousness of this near-collision situation.

Regarding Ship Pair 2 (MMSI 636021134 and 310499000) in Fig. 4(b), the position variable values are similarly placed in the 6 nm threshold, suggesting a crossing scenario. DCPA for this encounter is -1.71 nm, which places it in Collision risk level, emphasizing the high-risk nature of the proximity. Compared to Ship Pair 1, TCPA for this encounter is positive at 0.53 minutes, indicating that ships are still approaching their CPA. The positive value indicates a potential collision risk as the ships encounter. Dr, calculated as 4.44 nm based on latitude and longitude, reinforces the close proximity and converging paths, underscoring the need for vigilance and possibly evasive action.

TABLE V
PARAMETER CALCULATION RESULTS

Encounter Number	Ship	MMSI	DCPA (nm)	TCPA (minute)	Dr (nm)
1	Ship 1	636018336	0.59184	-0.34659	2.75345
	Ship 2	357203000			
2	Ship 1	310499000	-1.71045	0.52879	4.44362
	Ship 2	636021134			

The results in Table V show that DCPA and TCPA values are sensitive to changes in Dr, relative angles, ship bearings, and relative speeds. For both encounters, DCPA values in or near zero indicate a high-risk level. Encounter 1 has a particularly low DCPA value, showing a severe risk at a recent time point. Meanwhile, encounter 2, with a positive TCPA, confirms an approaching condition that requires preventive action

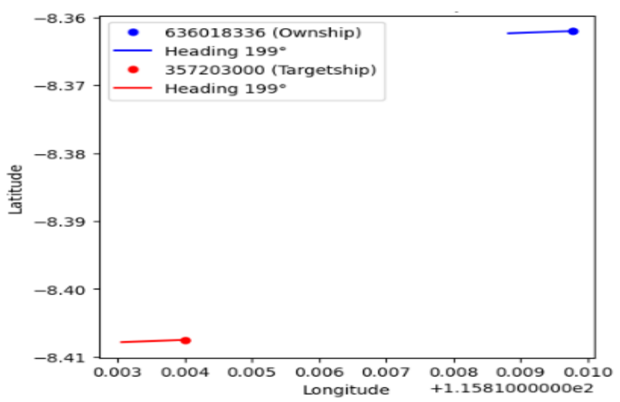
B. *Identify the Ship Encounter Situation*

In this study, the identification of ship encounter situations depends on a quantitative interpretation of the relative course and relative bearing values between two ships, as shown in Table II. These navigational parameters provide the basis for classifying encounter types and defining appropriate navigational actions according to international maritime regulations. In this section, the classification of ship encounters based on data in Table V was discussed in detail, with the results clearly summarized in Table VI and further visualized in Fig. 5 to support accurate situation analysis.

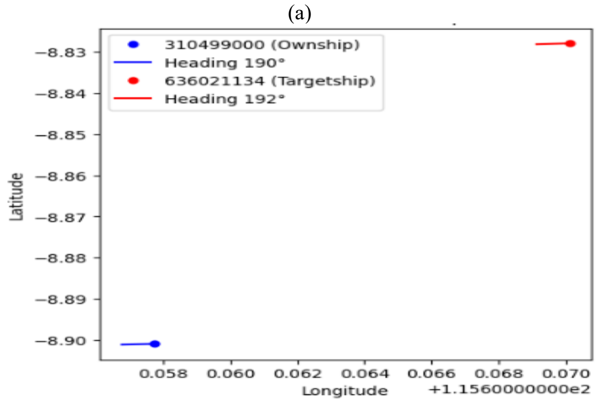
TABLE VI
SITUATION RESULTS OF SHIP ENCOUNTERS

Encounter Number	Ship	Relative Course	Relative Bearing	Situation
1	Ship 1 Ship 2	0.59	0.35	Crossing gives way to ship passing at the bow
2	Ship 1 Ship 2	1.71	0.53	Crossing gives way to ship passing at the stern

Understanding and accurately classifying encounter situations, such as crossing scenarios, are essential components of collision risk assessment in maritime navigation. The analysis in Table VI, based on relative course and bearing values, classifies both encounters in this study as crossing situations. The classification is shown in Fig. 5, offering a detailed depiction of each ship positioning and the navigational responsibilities presented by COLREGS framework. These results show the importance of role designation in managing collision risk effectively



(a)



(b)

Fig. 5. Ship encounter situations: (a) Crossing, give-way ship passes at the bow; (b) Crossing, give-way ship passes at the stern.

In Encounter 1 (Fig. 5(a)), Ship 1 (OS) and 2 (TS) are positioned in a crossing scenario, as determined by a relative course of 0.59 and a bearing of 0.35. In this configuration, Ship 1, designated as the give-way ship, is required to yield to Ship 2, acting as the stand-on ship. The arrangement is shown in Fig. 5(a), with OS (in blue) positioned to pass in front of TS (in red). The respective headings of each ship are indicated by colored lines, confirming the obligation of OS to adjust its speed or course to maintain a safe distance when passing ahead of TS. This scenario shows a typical crossing encounter, where the give-way ship is obligated to take proactive measures and prevent a potential collision.

Ship Encounter 2 (Fig. 5(b)) presents a crossing situation, although with a different relative positioning compared to Encounter 1. Specifically, Ship 1 (OS) and Ship 2 (TS) have a relative course of 1.71 and a relative bearing of 0.53, placing OS behind TS. In this configuration, OS, must adjust its course or speed to pass behind the stand-on ship (TS), which maintains heading and speed as shown in Fig. 5(b). The visualization emphasizes the role of OS in maneuvering to avoid crossing in front of TS and adhering to navigational protocols to ensure a safe distance. This situation further shows how different relative positions in crossing scenarios impact the actions required from the give-way ship.

In both Encounter 1 and Encounter 2, the classification of the situations as crossing encounters, along with the consistent designation of Ship 1 as the give-way vessel, highlights the critical importance of interpreting relative course (ϕ) and bearing (α) accurately in maritime collision risk assessment. As detailed in Table VI and illustrated in Fig. 5, this analytical approach clarifies each ship's navigational responsibility, reinforcing compliance with COLREGS, particularly Rules 15 and 16. Such clarity is essential for ensuring coordinated actions between vessels. By following their designated roles based on encounter geometry, ships can effectively reduce the likelihood of dangerous proximity and miscommunication. This classification method enhances situational awareness and reinforces proactive collision avoidance behavior, particularly in congested maritime zones or restricted waters where decision latency can significantly elevate operational risk.

C. *CRI Assessment*

CRI serves as a key measure for assessing potential ship collision in maritime navigation. This section builds on the encounter situations identified in Section B and introduces F-AHP to enhance the precision and reliability of CRI assessment. Although conventional AHP methods are effective, there are challenges when parameter values fall between thresholds, causing ambiguity in risk categorization. By integrating fuzzy logic, F-AHP resolves ambiguities through fuzzy membership functions, ensuring a smooth transition between risk categories and producing crisp values for decision-making [28][29]. This method has been widely applied in decision-making tasks where uncertainty and overlapping criteria are prevalent [30].

CRI calculation incorporates DCPA, TCPA, and Dr values as shown in Table VII, following the method outlined in Equation (10). Parameter weights were assigned based on their significance in collision prediction, as derived from AHP framework. Previous studies [10] identified TCPA as the most critical parameter, with a weight of 0.525, followed by DCPA (0.334), and Dr (0.142). To enhance the evaluation process, thresholds for minimum safe distance (0.5 nm) and time (15 minutes) [31], were integrated into F-AHP model. The thresholds ensure the correlation of CRI calculations with established maritime safety standards, thereby influencing the degree of membership for each parameter. This is to ensure that CRI categorization is in line with established safety standards. The incorporation of fuzzy logic refines the input values into a crisp CRI score, classifying collision risk into three levels, namely high (CRI > 0.667), moderate (0.333 ≤ CRI ≤ 0.667), and low (CRI < 0.333), as shown in Fig. 2. The integration of fuzzy logic refines these inputs into a crisp value, categorizing each CRI level, as presented in Table VII.

TABLE VII
CRI CALCULATION RESULTS

Encounter Number	1	2
DCPA (nm)	0.59	-1.7
TCPA (minutes)	-0.34	0.53
Dr (nm)	2.75	4.44
CRISP Value DCPA	1.3	1.3
CRISP Value TCPA	11.5	11.5
CRISP Value Dr	3	3
Situation	Crossing, the give-way ship passes at the bow	Crossing, the give-way ship passes at the stern
CRI	0.361	0.361
Level	Threat	Threat

Table VII provides a summary of the CRI calculations for the analyzed ship encounters. In Encounter 1, the input values for DCPA, TCPA, and Dr were 0.59 nm, -0.3 minutes, and 2.75 nm, respectively. These raw values were refined through F-AHP process, which applied fuzzy membership functions to resolve uncertainties. The defuzzified crisp values were calculated as 1.3 nm, 11.5 minutes, and 3 nm for DCPA, TCPA, and Dr, respectively. Based on these values, DCPA and TCPA were classified at Collision level, while Dr was categorized at Threat level. CRI value was 0.361, placing the encounter in Threat category. This process ensures consistent classification of risk levels, providing mariners with clear guidance for decision-making in real-time navigation.

CRI levels derived from F-AHP model provide actionable insights that are in line with COLREGS rules, particularly rule 15 (Crossing Situation) and 16 (Action by Give-Way Ship). In Encounter 1, ship 1 must adjust its course or speed to pass safely ahead of the stand-on ship 2. Meanwhile, the stand-on ship should avoid crossing in front of the give-way ship. The refined CRI values offer clear and reliable assessments of potential risks, enabling ship to take proactive measures to avoid collision. By incorporating F-AHP, this method enhances the consistency and reliability of CRI calculations, supporting safer and more effective navigation in challenging maritime environments.

D. Comparative Analysis of Collision Risk Assessment

Section D evaluates the performance of AHP and the proposed F-AHP in CRI measurement, showing their differences through Table VIII, Fig. 6, Fig. 7, Fig. 8, Fig. 9, and Fig. 10. Although AHP effectively weights parameters, it often faces challenges with ambiguities near linguistic category boundaries and conflicting parameter interpretations. F-AHP addresses these challenges by incorporating fuzzy membership functions and defuzzification, producing CRI values that are more sensitive, accurate, and correlated with real-world ship dynamics.

Table VIII compares CRI values calculated using AHP and F-AHP across four ship encounters. Although AHP depends on fixed thresholds for categorization, F-AHP refines ambiguous parameter values into definitive linguistic categories such as Collision (C), Danger (D), Threat (T), and Attention (A). The sensitivity of F-AHP suggests that the refinement in DCPA values from the ambiguous thresholds in AHP (DCPA for Encounter 1 adjusted from 0.59 to 1.3 causes a CRI that transitions from Attention (0.178) to Threat (0.361). Across all analyzed ship encounters, F-AHP consistently reduces classification ambiguity, with an average of 40% improvement in sensitivity for high-risk scenarios. To further show these refinements, Fig. 8 shows the differences in DCPA, TCPA, and Dr values across AHP and F-AHP, with shaded regions representing the linguistic ranges for each parameter. The graph shows that the refinement process applied by F-AHP, where parameters such as DCPA (from 0.59 to 1.3) and TCPA (from -0.34 to 11.5) are adjusted to reflect real-world ship dynamics. These refinements not only address the inconsistencies observed in AHP classifications but also enhance compliance with COLREGS Rule 15 by providing clearer thresholds for preventive actions. The shaded regions in Fig. 7 validate fuzzy membership ranges applied, ensuring that CRI values correlate with safety-critical scenarios.

Fig. 6, Fig. 8, Fig. 9, Fig. 10 provide visual validation of the numerical refinements presented in Table VIII. Specifically, Fig. 8 and Fig. 9 show how F-AHP refines ambiguous CRI values in crossing scenarios, resolving parameter misclassifications that arise with AHP. Building upon the results, which show the limitations of AHP in detecting collision risk, Fig. 6 and Fig. 10 further validate the superiority of F-AHP in handling complex maritime scenarios, specifically addressing head-on and overtaking encounters. The scenario is characterized by the relative course (ϕ) and bearing (α) of vessels, as defined in Table II, which are critical indicators in determining encounter types. Furthermore, Fig. 11 and Fig. 12 introduce the results of discrete event simulation (DES), offering a dynamic perspective on how CRI values evolve over time in response to ship movements. Fig. 11 presents a simulation of ship movement under an overtaking scenario, showing how F-AHP provides an earlier and more sensitive CRI warning compared to AHP, allowing for more timely navigational decisions. Fig. 12 further validates the impact of F-AHP by comparing CRI trends between AHP and F-AHP in ship movement simulation.

In Ship Encounter 1, AHP classifies the Collision Risk Index (CRI) as 0.178 (Attention), based on DCPA = 0.59 (Collision), TCPA = -0.34 (Attention), and Dr = 2.75 (Threat). However, the visual evidence in Fig. 8 contradicts this classification, as it clearly shows both ships moving along the same heading (199°) with the target ship (TS) directly ahead of the ownship (OS). This indicates a potentially hazardous overtaking situation. When the same data is re-evaluated using F-AHP, the TCPA is adjusted to 11.5 (Collision) and DCPA to 1.3 (Collision), resulting in a revised CRI of 0.361 (Threat). This updated classification is more consistent with the spatial arrangement depicted in the simulation. The numerical shift confirms that AHP underrepresents the risk in scenarios where course and speed similarities create persistent convergence. The recalculated CRI under F-AHP thus reflects the actual collision potential observed in the plotted trajectory, particularly where the ships maintain close proximity without sufficient lateral separation. Fig. 8 validates that the refined output better corresponds to the real encounter geometry and supports the need for further cautionary action in this specific case.

Ship Encounter 2 (Fig. 9) provides further compelling evidence of the limitations associated with traditional AHP in managing conflicting parameter values in collision risk scenarios. In this encounter, AHP calculates a CRI of 0.105 (Attention), based on DCPA = -1.7 (Attention), TCPA = 0.53 (Attention), and Dr = 4.44 (Attention). The negative DCPA value implies that the vessels have already passed their closest point of approach and are diverging. However, visual inspection in Fig. 9 contradicts this assumption; it clearly illustrates that both vessels are still on converging paths, indicative of a continuing collision threat. This discrepancy underscores the potential for misclassification when relying solely on AHP's rigid thresholding system. Upon applying F-AHP, the DCPA is refined to 1.3 (Collision), TCPA to 11.5 (Collision), and Dr to 3.0 (Threat), producing a revised CRI of 0.361 (Threat). These updated parameter values align closely with the spatial configuration shown in Fig. 9, where the ownship (OS) and target ship (TS) remain in close proximity along nearly parallel headings. The recalculated CRI more accurately reflects the actual navigational context and highlights a substantial risk that requires action. The refinement demonstrates F-AHP’s capacity to correct underestimations inherent in AHP, particularly in cases involving ambiguous trajectory interpretations. The consistency between numerical results and visual evidence reinforces the advantage of F-AHP in providing operationally meaningful classifications. This encounter confirms fuzzy logic enhances reliability and precision in maritime risk assessment.

Fig. 10 shows a head-on encounter scenario. In this case, AHP assigns a CRI of 0.14 (Attention), based on DCPA = 3.1823, TCPA = 0.5921, and Dr = 3.6. Although the values indicate a moderate level of risk, AHP fails to accurately capture the high-risk trajectory observed in the scenario. F-AHP refines these parameters to DCPA = 1.3 (Collision), TCPA = 11.5 (Collision), and Dr = 3.0 (Threat), recalculating CRI to 0.36 (Threat). The refinement is in line with COLREGS Rule 14, which requires early and decisive action in head-on situations. By addressing the ambiguity inherent in AHP, F-AHP provides clearer and more actionable guidance to navigators, facilitating timely compliance with COLREGS Rules 14, 15, and 16.

Fig. 6 shows an overtaking scenario governed by COLREGS Rule 13. The rule specifies that the overtaking ship should keep clear of the other. Specifically, AHP assigns CRI of 0.14 (Attention), based on parameter values of DCPA = 1.6446, TCPA = -0.4459, and Dr = 3.0323. This classification underestimates collision risk, as the negative TCPA fails to adequately show the proximity of the overtaking ship. In comparison, F-AHP refines these parameters to DCPA = 1.3 (Collision), TCPA = 11.5 (Collision), and Dr = 3.0 (Threat), recalculating CRI to 0.36 (Threat). The reclassification is more accurate with the overtaking dynamics shown in Fig. 6, enabling navigators to take early and decisive actions to avoid potential collision.

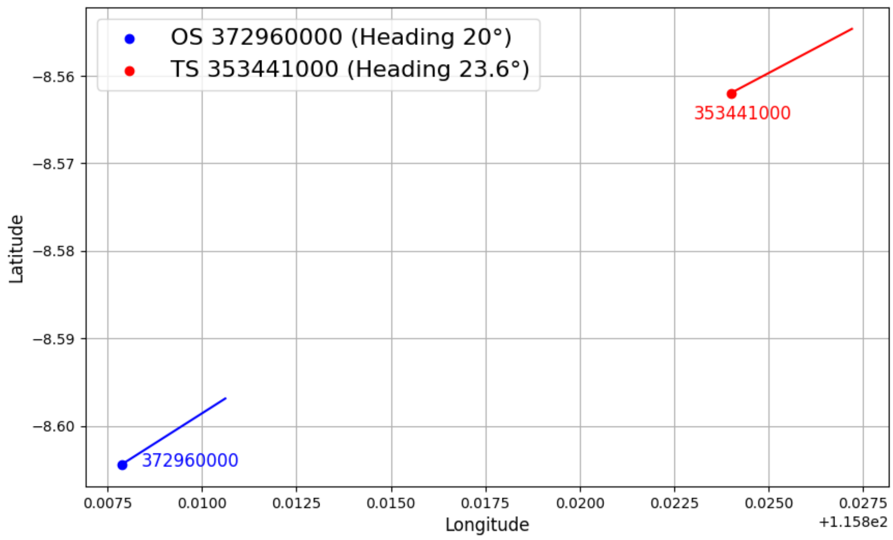


Fig. 6. Simulation of ship encounter 6.

To evaluate the significance of F-AHP refinements in real-time maritime navigation, a discrete event simulation (DES) was performed. The results, presented in Fig. 11, demonstrate the effectiveness of F-AHP in computing the Collision Risk Index (CRI) during simulated ship movements. The simulation models ship trajectories under constant speed and heading, allowing their relative positions to evolve dynamically. This approach aligns with prior research in maritime traffic risk assessment [32], where real-time trajectory updates are used to assess collision risks more accurately. Furthermore, the simulation provides temporal insights into how CRI values fluctuate as ships approach or diverge, highlighting periods of elevated risk. By continuously monitoring CRI in a dynamic setting, the simulation reveals the added precision of F-AHP in capturing transitional risk states that conventional methods might overlook. This dynamic evaluation enhances decision-making in navigational control systems under uncertainty.

Based on the results, the initial Dr between ships is 2.75 nautical miles (nm), with OS traveling at 12.7 knots and TS at 12 knots, both on a heading of 199°. As the simulation progresses, an overtaking situation occurs, governed by COLREGS Rule 13. This rule mandates that the overtaking vessel must keep clear of ship being overtaken. In the initial condition, AHP calculates CRI of 0.178 (Attention), while F-AHP refines CRI to 0.361 (Threat). This difference illustrates the limitations of AHP's rigid threshold approach, which may underestimate early-stage risks in overtaking scenarios. F-AHP, using fuzzy membership functions, identifies elevated risk earlier, enabling timely navigational responses such as speed adjustments or course alterations. Its enhanced sensitivity supports proactive collision avoidance aligned with COLREGS. The dynamic performance of F-AHP is further demonstrated in Fig. 12, where CRI values over time confirm its superiority in tracking and responding to evolving encounter conditions compared to conventional AHP-based evaluations.

The graph in Fig. 12 compares CRI values calculated using AHP and F-AHP over multiple time steps. CRI values for AHP show fluctuations, indicating inconsistency in risk assessment. In comparison, CRI values for F-AHP remain constant at 0.361, suggesting a stable and refined risk assessment method. This consistency in F-AHP shows the ability to provide reliable and early risk detection without abrupt changes in classification. To statistically validate the significance of F-AHP in CRI calculation, a paired t-test was conducted between CRI values obtained using AHP and F-AHP. The results showed a t-statistic of 5.1315 and a p-value of 0.0068, indicating a statistically significant difference between the two methods. Since the p-value is well below the standard threshold of 0.05, F-AHP is considered to provide significantly different and more stable CRI assessments compared to AHP [33]. This result confirms that F-AHP enhances sensitivity in collision risk assessment, ensuring early identification of potential risk more consistently.

The explanation provided by Table VIII as well as Fig. 6, Fig. 7, Fig. 8, Fig. 9, and Fig. 10 show that F-AHP enhanced capability can refine parameter values near linguistic thresholds. This shows that CRI values accurately reflect real-world ship dynamics and risk levels. Table VIII underscores the recalibration of ambiguous AHP parameters such as DCPA, TCPA, and Dr into definitive linguistic categories like Collision and Threat, effectively resolving misclassifications inherent in AHP. Fig. 7 visually validates the refinements, showing how F-AHP correlates ambiguous values with precise risk categories. These improvements are further substantiated by Fig. 6, Fig. 8, Fig. 9, and Fig. 10, where recalibrated CRI values consistently correlate with observed ship dynamics across crossing, head-on, and overtaking scenarios. For example, in crossing encounters (Fig. 8 and Fig. 9), F-AHP accurately identifies elevated risk levels that AHP underestimates. Head-on and overtaking encounters in Fig. 10 and Fig. 6 show F-AHP's superior sensitivity and accuracy in detecting and classifying high-risk situations, fully complying with COLREGS Rules 13, 14, 15, and 16. To extend the analysis beyond static cases, Fig. 11 and Fig. 12 introduce a discrete event simulation to evaluate CRI variations over time.

The results indicate that despite the fluctuation of AHP CRI, F-AHP maintains consistent and stable values, showing a more reliable risk assessment. The statistical analysis using a t-test ($t = 5.1315$, $p = 0.0068$) confirms the significant difference between AHP and F-AHP. This confirms that F-AHP provides statistically valid improvements in collision risk evaluation. The practical implications of these results are substantial. The ability of F-AHP to provide consistent and sensitive CRI values suggests its potential integration into real-time vessel traffic management systems (VTMS) and autonomous navigation platforms. Compared to conventional AHP-based models, which are limited in handling parameter ambiguities, F-AHP offers a more robust framework for early-warning systems.

V. Conclusion

In conclusion, this study showed that F-AHP enhanced maritime collision risk assessment by refining key parameters such as DCPA, TCPA, and Dr, to improve the sensitivity and accuracy of CRI calculations. Comparative analyses between AHP and F-AHP, as presented in Table VIII, Fig. 6, Fig. 7, Fig. 8, Fig. 9, Fig. 10, showed that F-AHP significantly reduced misclassification issues in conventional AHP-based models. The results from Fig. 11 and Fig. 12, supported by discrete event simulations, further confirmed that F-AHP provided stable and higher CRI values in critical scenarios, ensuring earlier and more accurate risk detection. Statistical validation using a paired t-test ($t = 5.1315$, $p = 0.0068$) confirmed the significant difference between AHP and F-AHP. This showed the role of F-AHP in improving maritime safety by reducing classification ambiguity and enhancing risk detection capabilities.

The results indicated that integrating F-AHP into maritime decision-support systems could enhance real-time collision avoidance in complex environments. The method aligns with COLREGS and provides early, actionable insights for navigators. Further studies are encouraged to assess F-AHP scalability in congested waters and its integration with autonomous navigation systems and AI-based predictive risk assessment frameworks.

APPENDIX

TABLE VIII A.1
COMPARISON RESULTS OF CRI VALUES

Encounter Number	AHP				F-AHP			
	DCPA	TCPA	Dr	CRI	DCPA	TCPA	Dr	CRI
1	0.59 (C)	-0.34 (A)	2.75 (A)	**0.178 (A)**	1.3 (C)	11.5 (C)	3 (T)	**0.361 (T)**
2	-1.7 (A)	0.53 (C)	4.44 (A)	**0.105 (A)**	1.3 (C)	11.5 (C)	3 (T)	**0.361 (T)**
3	17.86 (A)	0.95 (C)	22.7 (A)	**0.037 (A)**	3.9 (T)	11.5 (C)	3 (T)	**0.197 (A)**
4	5.1 (A)	-1.46 (A)	12.3 (A)	**0.091 (A)**	3.9 (T)	11.5 (C)	3 (T)	**0.197 (A)**
5	-3.01 (A)	0.19 (A)	3.18 (A)	**0.11 (A)**	1.3 (T)	11.5 (C)	3 (T)	**0.361 (T)**
6	1.64 (A)	-0.45 (A)	3.03 (A)	**0.14 (A)**	1.3 (T)	11.5 (C)	3 (T)	**0.361 (T)**

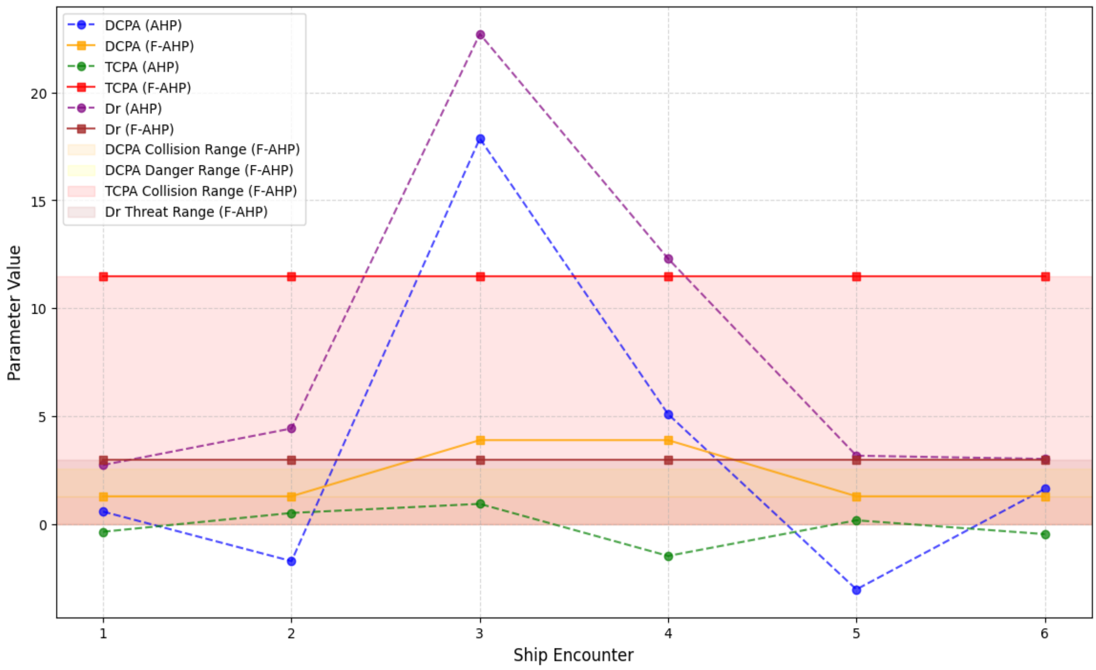


Fig. 7. Comparison of parameter values between AHP and F-AHP.

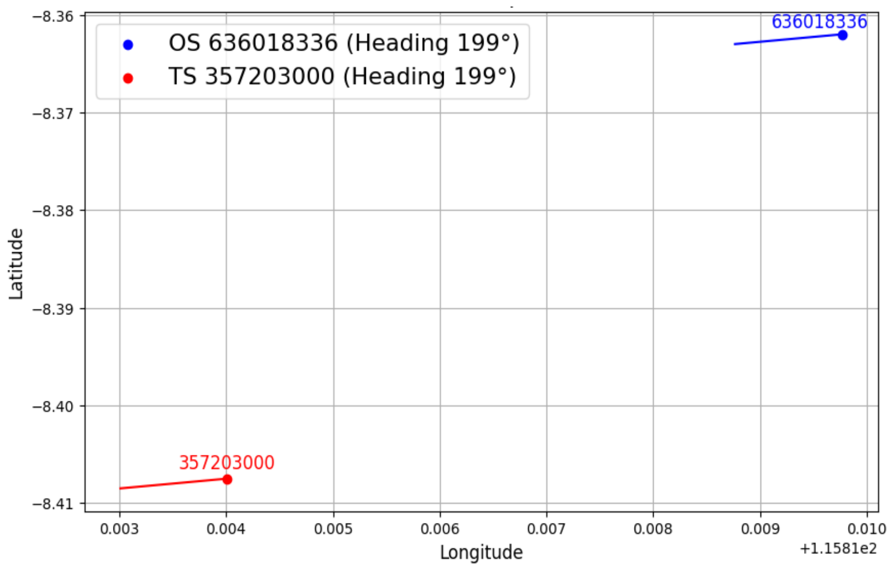


Fig. 8. Simulation of ship encounter 1.

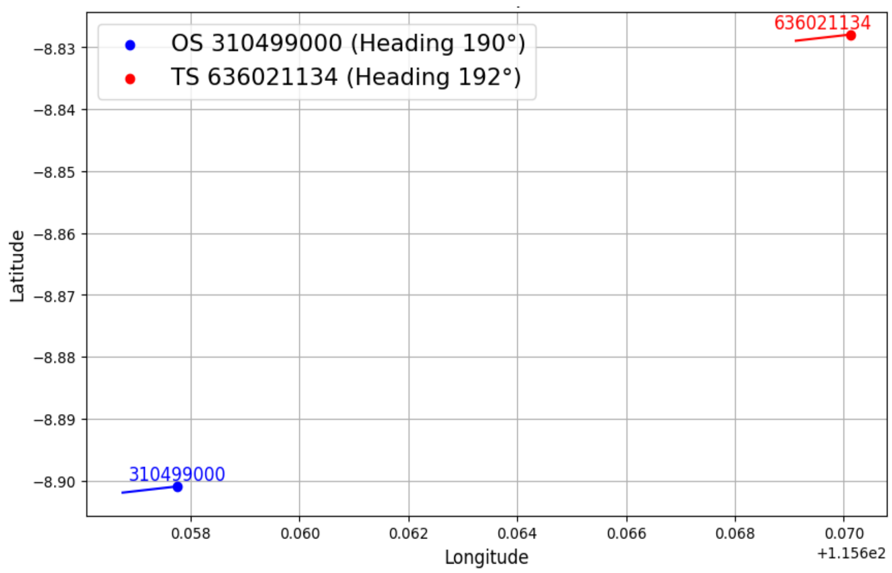


Fig. 9. Simulation of ship encounter 2.

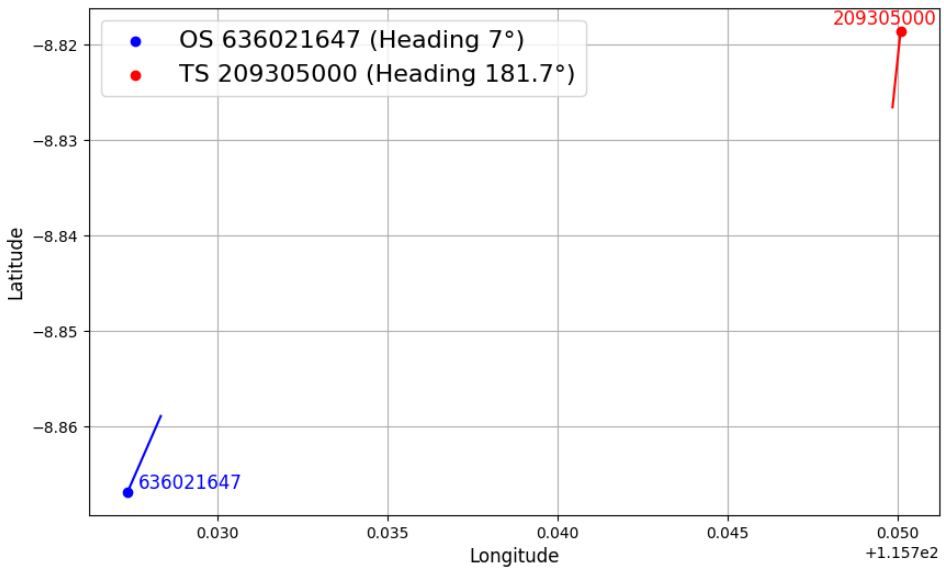


Fig. 10. Simulation of ship encounter 5.

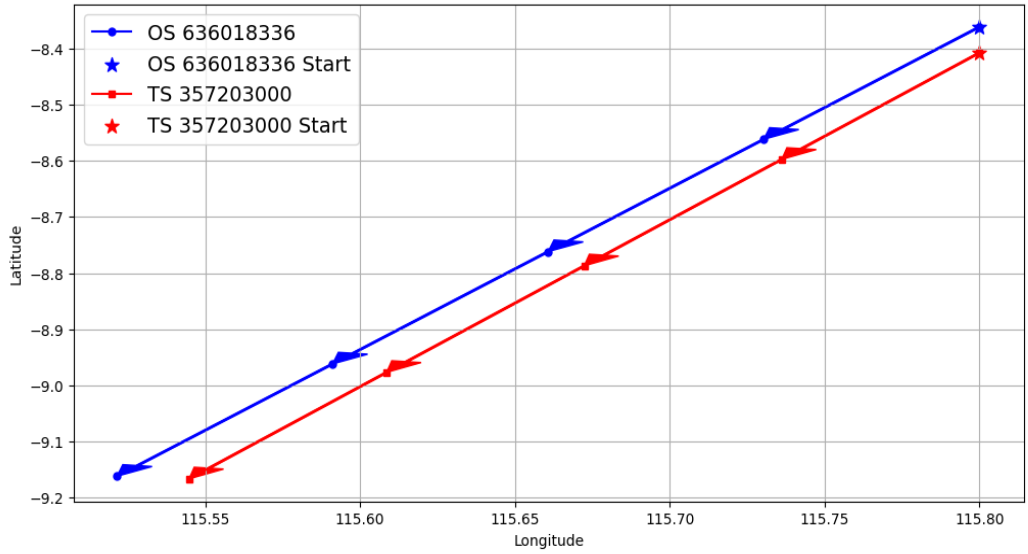


Fig. 11. DES-based simulation showing evolving CRI values under overtaking scenario.

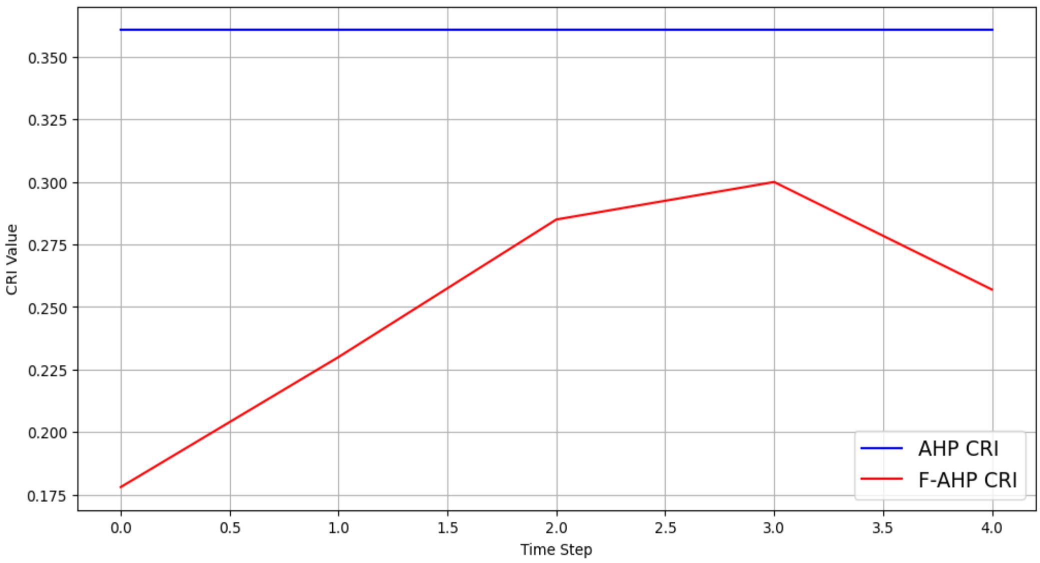


Fig. 12. Comparison of CRI values between F-AHP and AHP on simulation of ships movement.

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