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COOPERATIVE COLLISION AVOIDANCE FOR AUTONOMOUS VESSELS IN A MIXED TRAFFIC ENVIRONMENT

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ABSTRACT

The rapid advancement of autonomous vessels and communication technology promises safer, more efficient, and sustainable shipping solutions. While autonomous vessels (AVs) offer the potential to significantly reduce the number of accidents caused by human error, their successful integration into mixed environments hinges on their ability to navigate complex interactions with manual vessels (MVs) effectively. We study the dynamics of interaction between AVs and MVs under the lens of cooperative and non-cooperative behavior using a cooperative game theory model in a connected mixed environment. Different risk perceptions of AVs and MVs based on ship domains were considered for the estimation of collision risk for different vessel types in mixed traffic. Simulation results validate the proposed collision avoidance strategy in multiple scenarios, demonstrating that the cooperative game approach can help AVs to dynamically adapt their trajectories and effectively obtain collision-free paths amid complex interactions with various encountered vessels.

1. INTRODUCTION

Intelligent maritime transportation systems including vessel networking technologies (such as vessel-to-vessel (V2V) and vessel-to-infrastructure (V2I) communications) will lead maritime transportation to witness a transformative shift towards the integration of Autonomous vessels (AVs) in maritime traffic environments. AVs promise increased operational efficiency and enhanced sustainability through optimized route planning, reduced fuel consumption, and minimum idle time. The adoption of AVs in maritime transportation would drive progress toward a more sustainable and technologically advanced maritime industry while enhancing safety and efficiency in maritime waters.

While AVs promise the potential to significantly reduce the number of accidents caused by human error and minimize collision risks at sea, challenges remain (Chen et al. 2021). These challenges revolve around the effective integration of AVs alongside manual vessels (MVs) in mixed-traffic environments, where vessels with varying autonomy would interact within confined shared waterways. MV maneuvering in confined mixed traffic waters, in compliance with International Regulations for Preventing Collisions at Sea (COLREGs), will present challenges for AVs to effectively interpret COLREGs, estimate collision risks, and predict collision avoidance strategies of MVs. Varying levels of autonomy and risk perceptions of vessels in mixed traffic will manifest in the form of varied collision avoidance strategies in shared waterways, resulting in unpredictability and uncertainty in the environment. This problem will be further compounded in close proximity and busy waterway scenarios where the efficiency of AVs will be impacted in the presence of MVs, introducing complex interactions with various encountered vessels. The need to address the risk and safety issues in mixed traffic environments thus necessitates exploring effective cooperative collision avoidance strategies for autonomous vessels to ensure improved safety, efficiency, and reliability for AVs (Gong and Du 2018; Sun et al. 2020).

We propose a multi-AV cooperative collision avoidance framework using a coalition-based cooperative game theory model. The idea is to enable AVs to estimate the collision risks from encountered ships

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(including AVs and MVs), cooperate with other AVs by forming a coalition, and shift their trajectories if required to mitigate potential risks of collision. The study examines the performance of cooperative (coalition-based) collision avoidance strategies of AVs in comparison to independent collision avoidance behavior in mixed-traffic using simulation tests across multiple scenarios. In addition to addressing existing gaps in collision avoidance strategies for AVs, this research aims to facilitate the practical implementation of autonomous systems in real-world maritime environments by ensuring safer mobility practices in mixed-traffic environments.

The remainder of this paper is organized as follows. Section 2 discusses related works; Section 3 introduces problem description and practical considerations. Section 4 discusses collision risk and safety parameters considered in the study. The model description is given in Section 5, which is followed by simulation results and discussion in Section 6 and the conclusion in Section 7.

2. LITERATURE REVIEW

Collision avoidance for autonomous vessels is an active area in research. Most existing studies in the domain have focused on strategies that detect static and dynamic obstacles in the path of autonomous vessels and generate a collision-free path based on different encounter situations in complete autonomous frameworks (Chen 2019; Liang et al. 2019; Zhao 2019; Chen 2020; Wang 2021). However, only a few studies (Wang et al. 2023; Liu et al. 2022) have explored collision avoidance strategies in mixed traffic environments in maritime.

Furthermore, based on existing literature, research methods for collision avoidance can be studied under two categories: Artificial Intelligence (AI) based and rules-based decision-making. Methods based on AI have included the development of deep reinforcement learning (DRL) models that exhibit excellent performance in controlling complex systems, such as autonomous ships by deriving optimal policies through trial-and-error interactions with surrounding situations (Sutton and Barto 2018). Studies have incorporated these approaches including Q-learning and Deep Q-Networks (DQN) for collision avoidance in smart ships (Chen 2019; Zhao 2019; Chen 2020; Wang 2021; Zhou 2019). Besides, AI-based methods designed for individual robots can be expanded to function effectively across several robots (Zhang et al. 2021). Numerous studies have adapted single-agent reinforcement learning algorithms to multi-agent reinforcement learning (MARL) to study multiple autonomous vessels. This enables vessels to investigate their individual best strategies simultaneously. This thus becomes a potential method that can be extended to cooperative collision avoidance in mixed traffic scenarios as well. However, there exist limitations to these methods including poor model interpretability (Wu et al. 2020) and the curse of dimensionality as the number of players increases (Di and Shi 2021).

Rule-based decision-making methods are another potential method to model for collision avoidance. Hu et al. (2020) proposed a cooperative bypassing algorithm in mixed traffic for autonomous platoons and created a cooperative adaptive cruise control framework. The outcomes of the simulation demonstrated that the algorithm could raise the effectiveness and performance of the platoon. There are existing studies on the use of game theory models for cooperative decision-making for roadways (Ji and Levinson 2020), (Yu et al. 2018), (Fu et al. 2023; Jing et al. 2019). Furthermore, Wang et al. (2023) is one of a few studies in maritime that provides a collaborative collision avoidance strategy for autonomous ships under mixed scenarios using generalized reciprocal velocity obstacle (GRVO) algorithm. It focused on the implementation of the GRVO algorithm as a collision avoidance strategy in a mixed autonomy scenario. Our study however, aims to investigate the broader scope of the interaction dynamics and conflict resolution between autonomous and manual vessels using cooperative game theory in a connected mixed traffic environment. In this direction, we propose the potential of cooperative coalition-based collision avoidance framework for the safe maneuvering and interactions of autonomous vessels in mixed-traffic situations.

Previous research indicates (1) There is a notable gap in maritime literature concerning the interaction between multiple AVs and MVs for collision avoidance in mixed traffic scenarios; (2) While rule-based methods offer better interpretability in comparison to artificial intelligence-based approaches, research on rule-based methods for multi-AV cooperative collision avoidance in maritime mixed environments is limited; (3) Despite the extensive use of game theory in various domains, its application to multi-AV collision avoidance in maritime mixed traffic remains largely unexplored.

3. PROBLEM DESCRIPTION AND PRACTICAL CONSIDERATION

Safer mobility in mixed maritime navigation is multifaceted and critical for the safe integration of AVs into existing maritime environments. The presence of AVs in mixed traffic would involve complex interactions due to the diverse behaviors, intentions, and risk perceptions of MVs. This would create dynamic and complex encounter situations for AVs to navigate through, resulting in increased collision risks. The challenge comes from the need for AVs to effectively assess risk perceptions of MVs, identify potential encounters that need evasive actions (including shifting trajectories), and coordinate and collaborate with other AVs.

Identification of potential encounter scenarios by AVs in mixed-traffic environments is crucial for an effective collision avoidance strategy. These encounters can be defined using collision risk parameters and potential trajectory intersections that may arise due to evasive actions. We assume a three-parallel lane (trajectory) waterway environment to provide predefined routes for AVs and MVs (Figure 1). We identify three broad scenarios of potential risky encounters for an AV in such a maritime setup. First is the 'same trajectory scenario', where two vessels on the same trajectory, following each other, need to ensure minimum collision risk for safe maneuvering (Figure 2a). Any evasive action that requires AVs to shift trajectory in this scenario, may result in another two encounter scenarios that include: (1) merging scenario, where two vessels attempt to merge (shift) into a common lane from different lanes at the same time (Figure 2b); (2) shifting to the same lane scenario, where a vessel may depart from its current course and maneuver into the adjacent lane with existing vessels (Figure 2c). Each of these encounter situations requires AVs to effectively assess collision risk and adapt collision-free trajectories accordingly.

Addressing these challenges necessitates high situational awareness, collaborative efforts, and shared communication among AVs (assuming MVs to be uncontrollable), to ensure effective collision avoidance. Communication protocols and infrastructure including maritime cloud network, V2V, and V2I communication are expected to be capable of facilitating AVs to perceive, store and transmit essential motion state information along with information on vessel types and related distinct attributes (such as desired maximum speed and distance headway) (Wang et al. 2022). Our study assumes such a connected environment to be in place, in accordance with the COLREGs for the effective exchange of essential information between vessels. We suggest a collision avoidance framework for AVs where AVs exchange essential information on intended maneuvering decisions and ensure cooperative collision avoidance efforts with surrounding vessels.

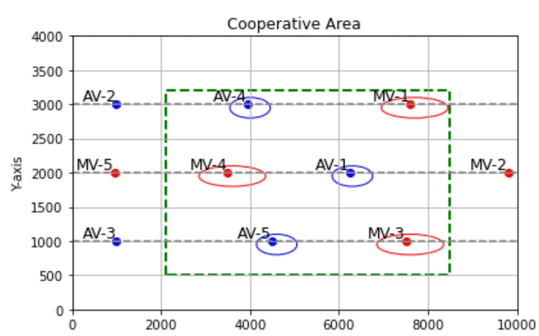
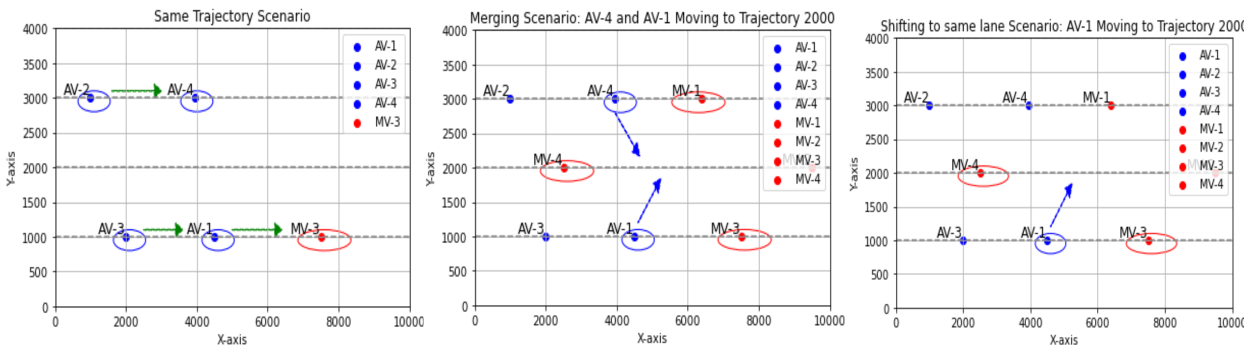


Figure 1: Waterway setup.



(a) Same trajectory scenario (b) Merging scenario (c) Shifting to same lane scenario

Figure 2: Encounter scenarios.

4. DESCRIPTION OF COLLISION RISK AND SAFETY PARAMETERS

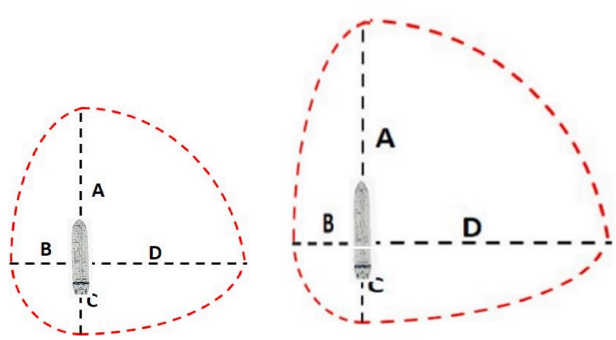
The identification of risky encounters by AVs requires the assessment of varied risk perceptions of MVs to estimate collision risk parameters. This section discusses the details of the ship domain and collision risk estimation considered in the study.

4.1 COLREG Compliant Ship Domain and Collision Risk Estimation in Mixed Traffic

We consider COLREG-compliant asymmetric elliptical ship domain and quantitative measures of collision risk (CR) to describe the safety of maneuvering decisions (Chun et al. 2021; Coldwell 1983).

4.1.1 Ship Domain

Each length of the ship domain is determined by considering the COLREGs, risk perceptions, and the maneuvering performance of the vessel (Ha et al. 2018, 2021). In a mixed traffic scenario, given the differences in autonomy levels, the risks perceived by MVs and AVs is expected to be different. This is considered using the varying sizes of the ship domain and the associated parameters (Table 1) for estimation of CR for each vessel type. In the ship domain, accounting for different risk perceptions, the lengths of A and D (Figure 3) are estimated to be equal to the desired distance headway preferred by the given vessel type. Lengths of B and C have defined dimensions (Chun et al. 2021). AVs are considered to be relatively less risk averse as compared to MVs and this is reflected in their smaller ship domain size due to relatively lower desired distance headway (Figure 3). a_{min} and a_{max} in Table 1 refer to the minimum and maximum acceleration considered in the study.



(a) AV (b) MV

Figure 3: Different ship domain sizes for AV and MV.

Table 1: Parameters for risk assessment.

Parameters	Values	Parameters	Values
a_{min}	$-2\ m^2$/s	A and D of ship domain for AV	940 m
a_{max}	6 m^2/s	B and C of ship domain for AV and MV	314 m
CR maximum	0.7	A and D of ship domain for MV	1500 m
Allowable CR (CR_{al})	0.3	Recognition distance (*dr*)	1000 m

4.1.2 Estimation of Collision Risk Factor

The closest point of approach (CPA) method evaluates CR factor (CR_{ij}) using the closest point between the two vessels (that is vessel i and vessel j) when vessels maintain current direction and current speed. In this study, the concepts of time at the closest point of approach (TCPA), and distance at the closest point of approach (DCPA) have been adapted from the existing study of Chun et al. (2021).

$$TCPA = \begin{cases} 0, & if\ ||V_i - V_j|| = 0 \\ \frac{(P_i - P_j).(V_i - V_j)}{||V_i - V_j||^2}, & Otherwise \end{cases}$$

$$DCPA = ||(P_i + V_i.TCPA) - (P_j + V_j.TCPA)||$$

$$CR_{ij} = exp\left(-\frac{DCPA}{a}\right).exp\left(-\frac{TCPA}{b}\right) \tag{1}$$

where,

$$a = -dr/ln\,(CR_{al})$$
$$b = -\frac{dr}{V_i}.ln(CR_{al})$$

P_i and P_j are position vectors and V_i and V_j are the speed vectors of vessel i and vessel j respectively. dr is the distance at which the vessel starts to recognize and monitor other vessels. CR_{al} is a collision risk value, which is set as a criterion to determine that the AVs should start to avoid other vessels.

A value of CR_{ij} equal to one indicates that vessel j is on the boundary of the ship domain of the vessel i, resulting in collision. CR_{ij} equal to zero indicates safe maneuvering. When the encounter scenario for an AV_i, includes more than one vessel, the collision risk factor for the vessel i, CR_i is calculated as follows:

$$CR_i = Max\ CR_{ij} \tag{2}$$

where CR_i denotes the maximum value of the collision risk factor between AV_i and the other vessels in the encounter scenario. Furthermore, the maximum CR threshold is defined as a threshold where collision risk is very high and AV would choose to give way (Table 1).

5. MODEL DESCRIPTION

We propose the application of cooperative game theory to intelligent autonomous vessels in a connected maritime environment to facilitate cooperative AVs to navigate through mixed traffic situations. In the proposed scheme, O_i is the set of vessels around AV_i; all AV players in O_i can connect and form coalition;

all the connected AVs and nearby MVs in a defined proximity area (represented as a dotted rectangle in Figure 1) influence the collision avoidance strategies of the AVs. The game played by vessel players in the coalition is a cooperative game, while the game played between any vessel player in coalition with any vessel player outside is a non-cooperative game (Fu et al. 2023). The game type is that of complete information.

The strategy in the proposed game theory model includes AVs in coalition to maneuver along their predefined trajectories while assessing the collision risks with evolving situations and dynamically taking evasive actions (change in acceleration and adapting the trajectories). These actions are determined using safety payoffs based on real-time information shared within the coalition. AVs in coalition reach the following agreements that satisfy individual and rationality conditions: (1) When there is a high collision risk conflict between two AVs, they adopt the cooperative game strategy, (2) For decisions on shifting trajectories, AV prioritize proximity to other AVs (over MVs), (3) When collision risk for AV is greater than maximum collision risk threshold, AVs choose to give-way.

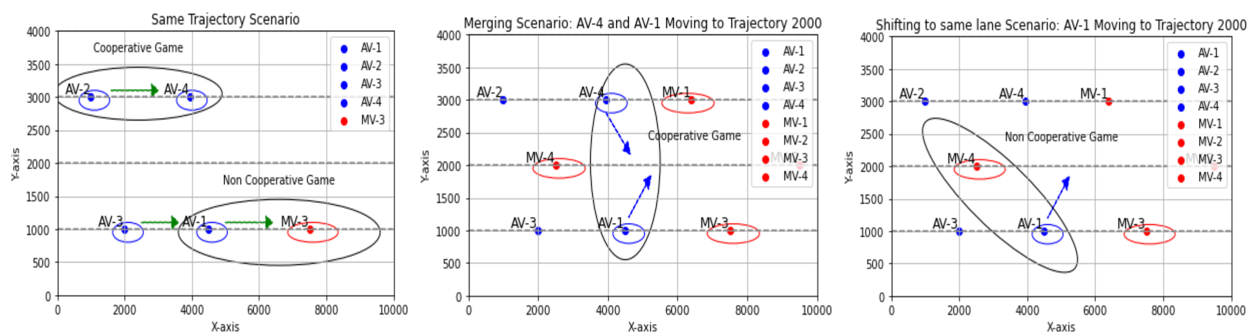
The payoff of each player (U_{Safety}) in the model is defined as the safety payoff for the chosen decision and is determined based on safety parameters including ship domain and collision risk factor (described in Section 4). It is estimated as the difference between the collision risk after the decision and the collision risk before the decision. It can be expressed as:

$$U_{Safety} = CR_{t=t_{ad}} - CR_{t=0} \tag{3}$$

where $CR_{t=t_{ad}}$ is the CR factor after the decision, $CR_{t=0}$ is the CR factor at a given time, t_{ad} is the time required to carry out the decision. The objective of the model is to maximize coalition safety payoffs, defined as overall safety payoffs of the AVs in the coalition. Coalition safety payoff is estimated as the sum of individual safety payoffs of all the vessels in the coalition across time t. It can be expressed as:

$$U(t) = \sum_{i=1}^{n} U^{i}{}_{safety}(t) \tag{4}$$

The safety payoffs, CR threshold and trajectory intersection conditions across the encounter scenarios (discussed in Section 3) identify multiple two-vessel conflicts in the environment. The resolution of these conflicts in these scenarios is described below (Figure 4).



(a) (b) (c)

Figure 4: Potential conflicts across scenarios.

Figure 4a illustrates the same trajectory scenario, where vessels maneuver in the same lane as other vessels, and conflicts may arise when a vessel i (AV-3) is in close proximity to the ship domain of the vessel in front (AV-1) (that is when CR factor for AV-3 becomes greater than max CR threshold). When such 'beyond threshold' CR conflicts arise between two AVs in the coalition, the game is cooperative while if such conflict emerges between an AV and an MV, it is solved using non-cooperative game. If the AV finds the safety payoff associated with shifting to the adjacent trajectory to be higher (representing a safer mobility alternative), the AV may consider shifting the trajectory after checking for the conflicts related to trajectory intersection that may result in merging or same lane change encounter scenario (Figure 2b, 2c).

Merging conflict arises when two vessels find shifting to a common trajectory to be a safer alternative in comparison to their current path at the same time (that is when safety payoffs associated with a common adjacent trajectory for both vessels are higher in comparison to their current path). Figure 4b describes the scenario resulting in merging conflict between the two vessels (AV-4 and AV-1). Such a conflict needs to be resolved before AVs implement the decision. Both vessels being AVs in coalition, exchange intended behavior and resolve conflict using cooperative game solutions.

Another possible encounter that an AV needs to consider before switching trajectory for safer alternatives, is the same lane change encounter (Figure 4c). The conflict arises when the preferred trajectory by AV is the same as the current trajectory of an existing vessel (that is, there exist vessels maneuvering in the preferred trajectory). Figure 4c illustrates AV-1 considering changing paths to another lane with an existing vessel on the lane (MV-4). This necessitates AV to resolve conflicts (if any) with those existing vessels before it decides to implement the change in trajectory decision. In this scenario, there may exist two possible types of conflicts: the high collision risk conflict with the vessel in the front and the vessel in the rear (MV-4 in this case) in the desired lane. AV compares the associated CR with both vessels and prioritizes resolving the high-risk conflict first, thus resolving the potential conflicts and ensuring proactive assessment of safety levels and effective collision avoidance.

Furthermore, based on the assumptions of the study, collision avoidance decision-making by AVs involves prioritizing the proximity to AVs over MVs due to their smaller ship domains and similar risk perceptions. Besides, in high-risk collision scenarios (when CR is greater than Max $CRij$), the AV chooses to be the give-way vessel (opting for speed adjustment or choosing to not opt for path change) to avoid collisions.

The conflicts identified are resolved using cooperative and non-cooperative games. The solution for a non-cooperative game (between AV and MV) is derived by maximizing the minimum payoff (Yu et al. 2018). However, when two vessels cooperate, the game solution includes maximizing the sum of payoffs of the vessels in conflict while ensuring that individual payoffs for vessels, in this case, are not less than the payoffs associated with a non-cooperative game. Each AV in a coalition chooses the decision (combination of acceleration values and the decision to shift trajectory) with the highest individual payoff, resulting in greater overall safety payoffs for the coalition. This decision combination of acceleration value and the decision to shift trajectory represents the collision avoidance game solution, derived from solving the cooperative and non-cooperative game between the vessels (Fu et al. 2023).

6. RESULTS AND DISCUSSION

The tests were designed as three simulation scenarios using Python to verify the significance of cooperative decision-making in collision risk mitigation. The simulation was allowed to proceed to compare the robustness and the safety payoffs of the coalition, in situations of collision risk exceeding one.

6.1. Simulation Setup

The simulation setup, consisting of four AVs and four MVs with predefined risk parameters (Table 2) is displayed using Figure 5.

Table 2: Risk parameters.

	Desired distance headway (m)	Expected maximum speed (Knots)
AV	940	15
MV	1500	10

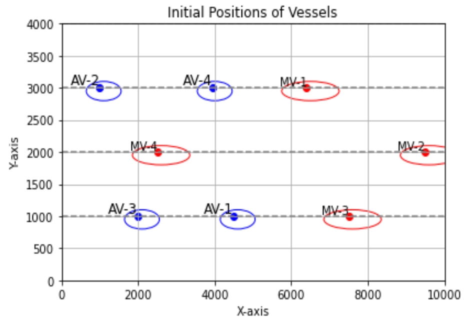


Figure 5: Simulation setup.

Simulation scenario 1 tests cooperative behavior among AVs based on the proposed cooperative game theory model, encouraging coalition formation and adaptive strategies for safe passage; Simulation scenario 2 explores non-cooperative (independent behavior), where AVs operate independently without forming a coalition, maximizing their own safety payoffs. In simulation scenario 3, AVs demonstrate cooperative behavior while encountering variable risk perceptions of MVs (with three MVs adhering to conservative risk perception and MV4 displaying different risk perceptions (Table 3). Simulation scenario 3 highlights the challenges posed by mixed traffic dynamics. Furthermore, MVs were considered to navigate with a risk-averse approach, maneuvering along predefined trajectories (without considering path changing). The simulations, conducted for over 20 iterations, compare the safety and risk parameters of a coalition of AVs, offering insights into the effectiveness of cooperative versus independent collision avoidance strategies in mixed-traffic environments.

Table 3: Details of simulation scenarios.

	Behavior of AVs	Risk parameters from MVs
Scenario 1	Cooperative	Desired distance headway = 1500*m*, Max expected speed = 10 knots
Scenario 2	Independent	Desired distance headway = 1500*m*, Max expected speed = 10 knots
Scenario 3	Cooperative	For MV-4, Desired distance headway = 1000*m*, Max expected speed =12 knots (Others, same as before)

6.2. Collision Avoidance by AVs in Different Scenarios

In scenario 1, all four AVs in the cooperative game theory model effectively avoided collisions during the simulation with the lowest maximum collision risk and highest coalition payoffs. Scenario 2 recorded the least coalition payoffs across iterations with maximum collision risk. Scenario 3 demonstrated the impact of the differential risk perceptions among MVs on the cooperative decision-making capability of the AVs-led coalition. Due to space restrictions, we restrict our explanation on the collision avoidance strategy for simulation scenario 1.

6.2.1. Analysis of Scenario 1

At the beginning of the simulation, AV-1 was on trajectory one (represented using y =1000) (Figure 6a). The proximity of AV-1 to MV-3's ship domain resulted in collision risk conflict between the two vessels. AV-1 played a non-cooperative game with MV-3 and chose to reduce the acceleration to ensure a safe distance, thus resolving the conflict and ensuring a safer state. Since MV-2 on trajectory 2 (y=2000) was far from AV-1 and the rear vessel MV-4 on trajectory two was outside the ship domain of AV-1, AV-1 had a higher payoff to shift the path to trajectory 2 to minimize collision risk with vessel MV-3. Considering the shift in trajectory, AV-1 played a non-cooperative game with MV-4 and could shift to a relatively safer position resulting in a reduced risk of collision (Figure 6b) It continues to maneuver in trajectory 2, while AV-2, AV-3, and AV-4 follow their predefined trajectories within coalition using cooperative games, ensuring minimum collision risk and safer mobility (Figure 6c). As the simulation proceeds, AV-1 plays a non-cooperative game with MV-2 due to the high collision risk from the same trajectory conflict between the vessels. On finding a relatively higher safety payoff for trajectory 3 with MV-1, AV-1 plays a non-cooperative game with MV-1 and succeeds in shifting trajectory to ensure reduced collision risk and higher safety payoffs (Figure 6d). Later, AV-3 and AV-4 consider shifting to trajectory 2 for higher safety payoffs at the same time, resulting in a possible merging conflict between the vessels. They resolve the conflict using the cooperative game and AV-3 decides to stay back, while AV-4 chooses to shift the trajectory, thus ensuring maximum total payoffs for the two vessels in the given scenario while minimizing collision risks (Figure 6e). AV-3 follows suit after AV-4 has successfully changed the trajectory (Figure 6f), thus ensuring effective collision avoidance and smooth maneuvering by AVs in the shared environment.

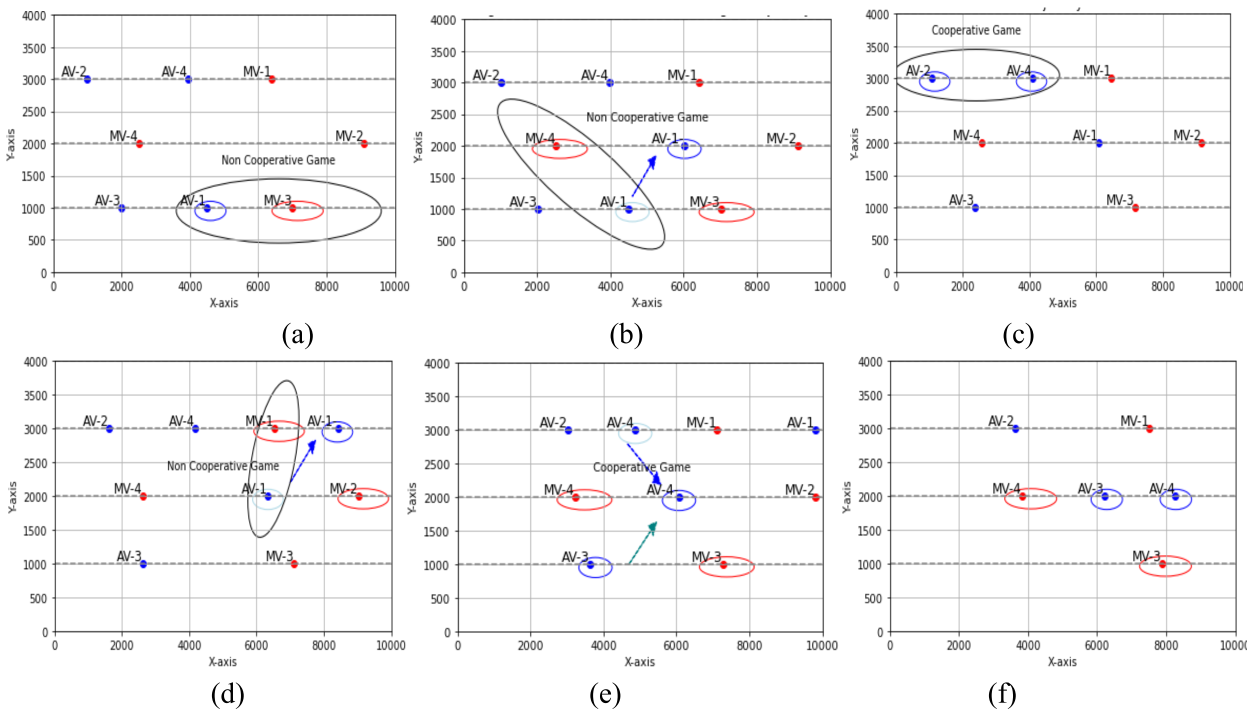


Figure 6: Simulation scenario 1: Collision avoidance analysis.

6.3. Comparison of Collision Avoidance Performance

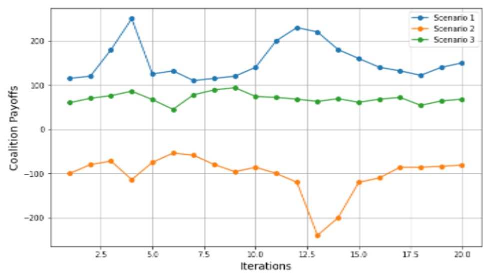
Collision avoidance performance was compared based on maximum collision risk and minimum distance recorded between vessels across three scenarios. Maximum collision risk was observed in scenario 2, followed by scenario 3, while scenario 1 outperformed the other scenarios, recording the lowest maximum risk. This indicates that proactive communication and cooperative behavior led coalition formation by AVs significantly reduced the collision risks as compared to other scenarios. Non-cooperative behavior among vessels (Scenario 2) resulted in higher collision risk with the smallest minimum distance among the vessels, displaying high collision risks and overall reduced safety levels. The minimum distance between vessels was the maximum for scenario 1, emphasizing the positive performance of the cooperative game theory model in ensuring safe navigation in mixed traffic situations.

6.4. Overall Payoff of the Coalition

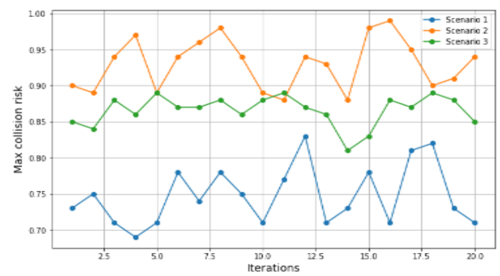
The coalition payoff for scenario 1 was higher than that of its initial state at t = 0 indicating that cooperative collision avoidance strategies had a positive effect on the safety levels of the AVs in the coalition. Scenario 3 recorded relatively lower coalition payoffs in comparison to scenario 1, displaying the complexity in navigation in the presence of the differential risk parameters of the MVs. Scenario 2 where AVs independently chose to avoid collisions while prioritizing their own safety recorded the least coalition payoff (the sum of safety payoffs for all AVs in the cooperative area was considered), indicating reduced safety and efficiency levels of the AVs.

6.5. Robustness

Simulation tests across iterations displayed the validity of the cooperative game theory model with cooperative collision avoidance strategies outperforming the independent risk mitigation behavior. (Figure 7a, 7b). To test the applicability of the model under different speed parameters (initial speed and expected maximum speed), we tested the model for predefined five different levels of initial speeds (8, 10,12,14, and 18 Knots) using the same simulation setup. The results were compared using coalition payoffs and maximum collision risk recorded across scenarios (Figure 7c, 7d). The results indicate the validity and superiority of cooperative behavior among AVs for all levels of different speeds, thus reflecting the robustness of the model.



(a)



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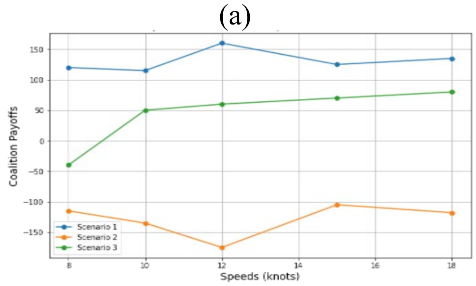
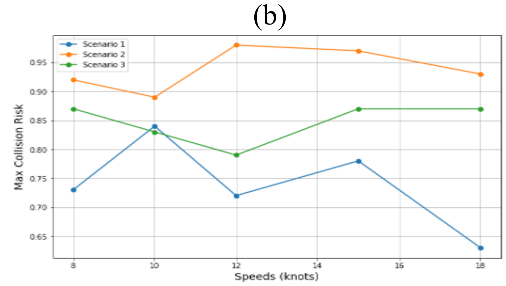


(c)



(d)

Figure 7: (a), (b) Coalition Payoffs and Maximum collision risk across Iterations; (c), (d) Coalition payoff and Maximum collision risk for simulation scenarios with different speeds.

7. CONCLUSION

This study proposed a cooperative collision avoidance decision-making framework based on the cooperative game theory model to improve the overall safety of AVs in mixed-traffic environments. We assumed that MVs in maritime are risk averse and uncontrollable (hence non-cooperative) and that the AVs in the model are cooperative. The payoffs of the players were determined using the COLREG-compliant ship domain and CPA method, considering the varied risk parameters in mixed traffic situations. Three broad maritime scenarios of the same trajectory, same lane changing, and merging conflicts among vessels were assessed under multiple two-vessel conflicts. Adaptive and cooperative trajectory shifts by AVs while addressing the potential conflicts are considered to be a fundamental collision avoidance strategy by AVs in mixed scenarios. The simulation results displayed a cooperative game model outperforming an independent decision-making framework. This emphasizes the significance of collective proactive behavior among AVs to mitigate potential collision risks in mixed maritime scenarios and contribute towards the overall safety and effective integration of AVs in maritime waters. Future scope of work includes extending the model to three and more player conflicts, introducing varied levels of perceived risks among MVs while allowing for random behavior and testing for complex scenarios.

REFERENCES

Ahn, S., M. Chitturi, D. Chen, and A. Noyce. 2017. "Towards Vehicle Automation: Roadway Capacity Formulation for Traffic Mixed with Regular and Automated Vehicles". *Transportation Research Part B: Methodology* 100: 196- 221.

Chen, C., X. Q. Chen, F. Ma, X. J. Zeng and J. Wang. 2019. " A Knowledge-Free Path Planning Approach for Smart Ships Based on Reinforcement Learning". *Ocean Engineering* 189:106299.

Chen, C., F. Ma, J. Liu, R. Negenborn, Y. Liu and X. Yan. 2020. "Controlling A Cargo Ship Without Human Experience Using Deep Q-Network". *Journal of Intelligent & Fuzzy Systems* 39(5): 7363–7379.

Chen, C., F. Ma, X. Xu, Y. Chen and J. Wang. 2021. "A Novel Ship Collision Avoidance Awareness Approach for Cooperating Ships Using Multi-Agent Deep Reinforcement Learning". *Journal of Marine Science and Engineering* 9(10): 1056.

Coldwell, T. G. 1983. "Marine Traffic Behaviour in Restricted Waters". *Journal of Navigation* 36:430–444.

Chun, D. H., M. I. Roh, H. W. Lee, J. Ha. and D. Yu. 2021. "Deep Reinforcement Learning-Based Collision Avoidance for An Autonomous Ship". *Ocean Engineering* 234: 109216.

Fu, M., S. Li, M. Guo, Z. Yang, Y. Sun, C. Qiu *et al.* 2023. "Cooperative Decision-Making of Multiple Autonomous Vehicles in A Connected Mixed Traffic Environment: A Coalition Game-Based Model". *Transportation Research Part C: Emerging Technologies* 157:104415.

Gong, S. and L. Du. 2018. "Cooperative Platoon Control for A Mixed Traffic Flow Including Human Drive Vehicles and Connected and Autonomous Vehicles". *Transportation Research Part B Methodology* 116:25–61.

Ha, J., M. I. Roh, L. Zhao, J. Eun, J. J. Park, and D. Y. Lee. 2018. "Risk Assessment and Avoidance of Marine Collision Using AIS Data". *In: Conference of Korean Association of Ocean Science and Technology Societies,* 261.

Hu, G., F. Wang, W. Lu, T. Kwembe and R. W. Whalin. 2020. "Cooperative Bypassing Algorithm for Connected and Autonomous Vehicles in Mixed Traffic". *IET Intelligent Transport System* 14 (8): 915–923.

Ji, A. and D. Levinson. 2020. "A Review of Game Theory Models of Lane Changing". *Transportmetrica A: Transport Science* 16 (3): 1628–1647.

Jing, S., F. Hui, X. Zhao, J. Rios-Torres and A. J. Khattak. 2019. "Cooperative Game Approach to Optimal Merging Sequence and on-Ramp Merging Control of Connected and Automated Vehicles". *IEEE Transactions on Intelligent Transportation System* 20 (11): 4234–4244.

Sutton, R. S. and A.G. Barto. 2018. *Reinforcement Learning: An Introduction*. The MIT Press.

Wang S., Y. Zhang, F. Song and W. Mao. 2023. "A Collaborative Collision Avoidance Strategy for Autonomous Ships under Mixed Scenarios". *Journal of Navigation* 76(2-3):200-224.

Wang, S., F. Ma, X. Yan, P. Wu and Y. Liu. 2021. "Adaptive and Extendable Control of Unmanned Surface Vehicle Formations using Distributed Deep Reinforcement Learning". *Applied Ocean Research* 110: 102590.

Wu, Z., K. Qiu and H. Gao. 2020. "Driving Policies of V2X Autonomous Vehicles Based on Reinforcement Learning Methods" *School of Internet of Things* 14(5): 331-337.

Yu, H., H.E. Tseng and R. Langari. 2018. "A Human-like Game Theory-Based Controller for Automatic Lane Changing". *Transportation Research Part C: Emerging Technologies* 88: 140–158.

Zhao, L. and M. I. Roh. 2019. "COLREGs-Compliant Multiship Collision Avoidance Based on Deep Reinforcement Learning". *Ocean Engineering* 191: 106436.

Zhang, K., Z. Yang and T. Baar. 2021. "Multi-Agent Reinforcement Learning: A Selective Overview of Theories and Algorithms". Springer.

Zhou, X., P. Wu, H. Zhang, W. Guo and Y. Liu. 2019. "Learn to Navigate: Cooperative Path Planning for Unmanned Surface Vehicles Using Deep Reinforcement Learning". *IEEE Access* 7: 165262-165278

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