Assessment of the Crew On-Duty Status Based on the Dynamic Probabilistic Risk Platform

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Abstract

Shipping operations are high risk, complex, and uncertain activities. And a ship collision can have catastrophic consequences. The behavior and status of the crew on duty are key factors that affect the navigation safety of the ship. This paper proposes a dynamic probabilistic risk platform of Maritime Accident Dynamics Simulation (MADS) and Information, Decision, and Action in a Crew context cognitive model (IDAC). The platform simulates the cognitive and decision making processes of the crew on duty in maritime incidents and dynamically analyzes the reliability of human decisions. It can predict events and their probability values that may lead to decision failures in knowledge driven task failure scenarios. The effectiveness of the platform is verified through a case study of a ship collision. The results show that the method can simulate dynamic critical scenarios of ship collision avoidance and achieve intelligent decision-making in a human centered system.

Introduction

Maritime has always been a high-risk, high-uncertainty industry. In the event of a maritime accident, there can be devastating consequences, including damage to people, property, and ecology (Xue et al., 2019). Studies have shown that 75-96% of shipping accidents involve human error, with the proportion of human or human factor-related accidents in collisions being even higher at 95% (Akyuz and Celik, 2014). In 1978, the International Convention on Standards of Training, Certification, and Watchkeeping for Seafarers (STCW) was adopted by the International Conference on Training and Certification of Seafarers (International Maritime Organization, 1978). The International Maritime Organization (IMO) also issued the Formal Safety Assessment (FSA) guidelines in 1996, which has become a common guideline for maritime safety management and has contributed to the improvement of shipping safety (Maritime Safety Committee, 2002; Montewka et al., 2014). However, actual accidents still suffer from insufficient consideration of human factors, over-reliance on expert judgment, insufficient data, and generalized methods. In this regard, the Probability Risk Analysis (PRA) method (Yang et al., 2013), which combines System Reliability Analysis, Human Reliability Assessment (HRA) (Hou et al., 2021), and uncertainty analysis methods, has received increasing attention. The PRA method is widely used in safety work in the U.S. aerospace, nuclear, marine, and offshore engineering fields (Mkrtchyan et al., 2015). However, the PRA approach relies too much on expert experience and tends to lead to incomplete risk setting for major accident scenarios, limiting the scope of its application. Therefore, researchers have proposed new PRA methods to overcome these difficulties, such as hybrid PRA and simulation-based PRA methods (N. Wang et al., 2020), and they are all dynamic PRA methods.

Dynamic PRA methods typically use time-dependent phenomenological system evolution models combined with stochastic behavior to estimate the probability of occurrence of various types of system responses to an initiating event (Aldemir, 2013). Among other things, system evolution models are used to track the current hardware state, process variable levels, operator states, and historical and time series of event scenarios (Siu, 1994). Due to the convenience in computer simulation and solution, discrete dynamic PRA methods are more widely used, such as Dynamic Discrete Event Tree (DDET) (Catalyurek et al., 2010), Accident Dynamic Simulator (ADS). DDET method is the basis of most discrete dynamic PRA methods, which are based on a time-dependent. The DDET method is the basis for most discrete dynamic PRA methods, which are based on a time-dependent system evolution model and various branching conditions to dynamically generate event trees and perform calculations. In essence, all discrete dynamic PRA methods use a simulation engine whose main function is to generate branches at each user-specified time step or condition and associated probabilities, and to calculate the probabilities of each branch node. This approach to dynamic simulation analysis provides a natural framework for designing human-mechanical-environmental safety analysis of complex systems, including a physical model of the operating environment, a mechanical model of the hardware failure, and a behavioral model of the operator's cognitive processes. A typical example is the Accident Dynamic Simulator with Crew Member Context model (ADS-IDAC) (Chang and Mosleh, 2007). ADS-IDAC can generate branch nodes of DDET using a limited number of rules, which in turn include the system hardware state, physical quantity changes, human decisions and operations, software failures or pre-defined end states. It can quantitatively and meticulously analyze the interaction response and consequences between human information, decisions and actions in a system and the system, and has been applied to safety and reliability analysis of nuclear power plants and human-caused reliability analysis of remote-control centers of intelligent ships.

This study presents an extended application of a cognitive model-based human factor reliability analysis method and a dynamic probabilistic simulation engine in the maritime industry. The study proposes a dynamic risk analysis platform, MADS-IDAC, which can simulate the cognitive and decision-making processes of the crew on-duty in maritime accidents and dynamically analyze the reliability of human decisions. The paper is organized as follows: Section 2 presents the basic methodological framework of the MADS-IDAC simulation platform components. Section 3 conducts a simulation experiment simulating a ship collision scenario as a case study. Section 4 discusses the results obtained from the case study. Finally, Section 5 summarizes the contributions of this study.

Method Framework

The PRA approach is utilized to enhance the prediction of decision failure events in risky scenarios by providing continuous scenario contextual information that combines the human-computer interaction impact of the duty officer and the system (Mosleh and Chang, 2004). The MADS-IDAC method is a combination of Maritime Accident Dynamics Simulation (MADS) and Information, Decision, and Action in a Crew context cognitive model (IDAC). This approach predicts the events and probabilities that may lead to decision failures in knowledge-driven task failure scenarios. MADS-IDAC generates a Discrete Dynamic Event Tree (DDET) by applying simple branching rules that simulate the crew's response in a maritime accident to changes in the target vessel and collision avoidance scenarios. The generated branches can be used to simulate the timing of decisions, the speed of task performance, the skipping of process steps, information synthesis processes that depend on the degree of memory and decision frameworks, manipulation of input information, and equipment failures. This method better reflects the information flow, synthesis, and task execution processes of the crew on-duty in response to maritime risk incidents.

Maritime Accident Dynamic Simulator Model Building

The MADS-IDAC system architecture consists of six modules: the crew on-duty module, control panel module, ship hydrodynamics module, ship navigation environment module, scheduler module, and user scenario control module. Figure 1 illustrates the interdependencies between these modules and their system architecture.

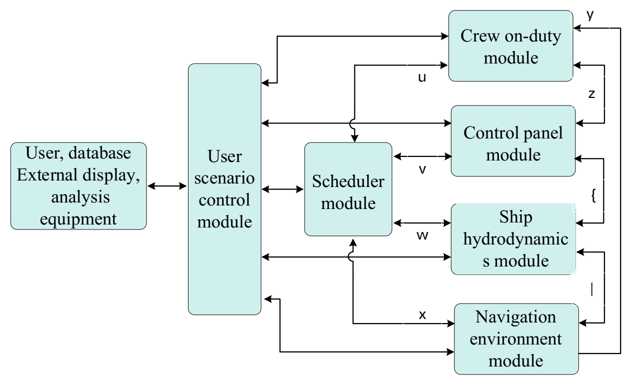

Figure 1: MADS-IDAC architecture diagram

The primary function of MADS is to generate branches of Discrete Dynamic Event Trees (DDET) under each user-specified time step or condition, calculate the probability of each branch node, and the related probability of nodes in DDET. It serves as the simulation engine of the system and operates within a dynamic PRA environment software. The criteria for generating branch nodes include system hardware status, changes in physical quantities, decisions, and operations of team members, software failures, or pre-set end states. This process ultimately generates a complete event flow model for the development of accident scenarios. This method of dynamic simulation analysis provides a natural framework for the safety analysis of complex systems.

Figure 2 shows the different scenarios generated dynamically by MADS-IDAC in a two-ship collision avoidance scenario with DDET. The decision-making events, safe scenario results, and collision results are presented in the discrete dynamic event tree. DDET commences from an initial event at a specific moment (zero point) and generates branches based on crew decision-making and ship state changes at discrete time points. The probability value of the complete scenario obtained is the product of the conditional probabilities of each branch. The branches of DDET are generated by changes that occur during the ship's voyage, such as speed and course changes, while human decision-making is reflected by human behavior towards the ship. The termination state of DDET represents either the ship's collision or arrival at the safe state.

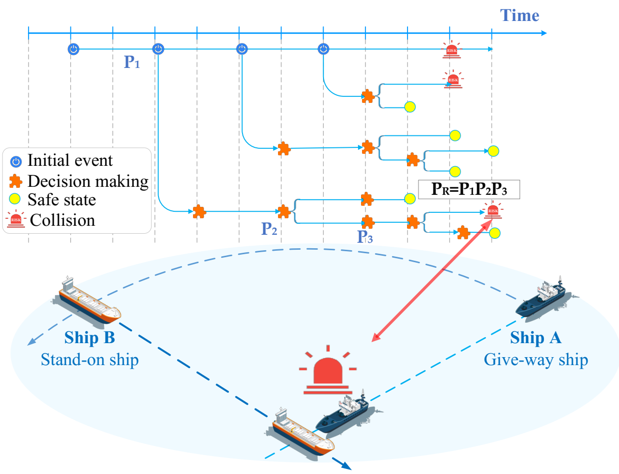

Figure 2: Discrete dynamic event tree generated by MADS-IDAC

The Cognitive Model Setting for the Crew-On Duty's Response in the Ship Collision Avoidance Task

Basic Concepts of the IDAC Model

The fundamental IDAC model depicts cognitive processes based on human cognitive behavior, specifically in the context of crew navigation and risk perception in the environment. Figure 3 illustrates the basic components and architecture of the IDAC model in the MADS dynamic PRA environment. The IDAC model comprises three components: information perception and processing (Information, I), decision-making (Decision, D), and action execution (Action, A). These cognitive processes involve working memory (WM), intermediate memory (IM), and knowledge base (KB), which collectively form a memory model.

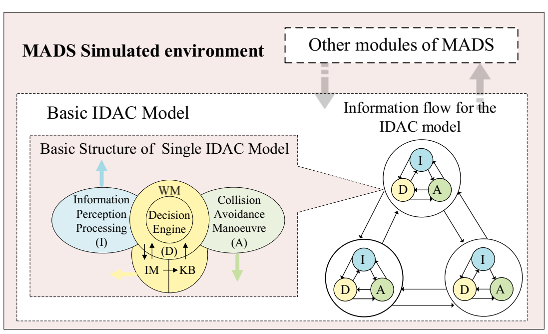

Figure 3: The basic composition and architecture of IDAC model

The latest perceived information is stored in WM, which has a limited capacity similar to human short-term memory. WM information is then transferred to IM for later retrieval. If the IM has an unlimited amount of memory space, however, the information might fade or decay over time. KB serves as a repository for all information about hardware systems and events that occur to the crew. It contains a collection of calculated procedures, current and past experiences for dealing with risks, and more.

The Performance Influencing Factor (PIF) is a core element of IDAC that directly affects its performance. PIF encompasses the physical, cognitive, and psychological responses of an individual and influences their cognitive-behavioral and decision-making abilities, which, in turn, directly affect the crew on-duty's status. This section was analyzed in detail in a previous study (Han et al., 2021).

Crew On-Duty Task Execution Process

The MADS-IDAC system utilizes a simplified three-person crew structure consisting of an Operator Decision Maker (ODM) representing the captain, an Operator Primary Actor (OPA) representing the chief officer, and an Operate Secondary Actor (OSA) representing the seaman. The ODM holds the highest decision-making authority and makes final decisions, while the OPA receives instructions from the ODM and performs preliminary judgment work. The OSA listens to orders. In analyzing ship accidents, such as collisions, the MADS-IDAC system supports three primary objectives: maintaining normal navigation, selecting the moment of collision avoidance, and making decisions. The specific objectives and strategies are chosen based on the perceived risk situation by the on-duty crew and their own PIF.

MADS-IDAC Software Platform Development

MADS-IDAC has been created based on Python (version 3.x), with the aim of achieving cross-platform functionality. To ensure compatibility with various hardware and software platforms, the engine has been integrated with Python.

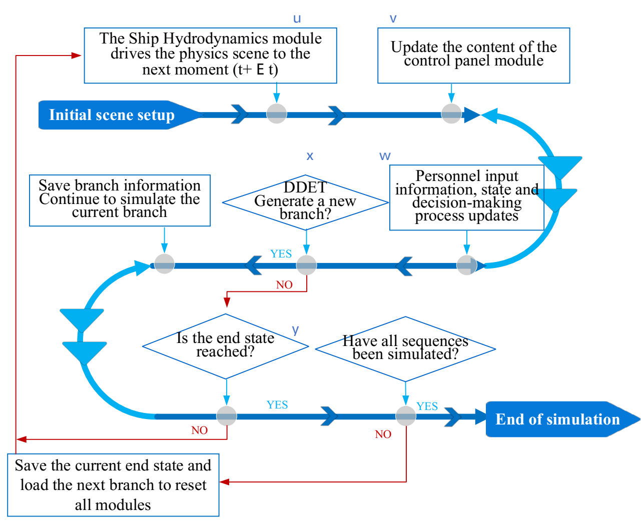

Figure 4: Simulation flow chart of MADS system

Ship No.	Initial Location		Initial Speed mile/h	Initial Heading Angle (Due North Direction as 0)
	Longitude	Latitude		
A	120.00	35.062	16	45
B	122.7463	35.618	14	335
C	121.4264	36.1451	13	198

Table 1. Case ship initial state setting

State No.	**System ID**	**Probability**	**End State**
End state 1	2112182007564344	0.836317	Safety
End state 2	2112182007577779	0.128062	Safety
End state 3	2112182007577278	0.027869	Safety
End state 4	2112182007573107	0.006064	Safety
End state 5	2112182007571372	0.001319	Safety
End state 6	2112182007572182	0.000367	Collision
	Total	Security end states：5 Collision：1	

Table 2. Simulation results of collision avoidance

Figure 4 illustrates the simulation flow process of the MADS system. For further information regarding the development of the software platform system, please refer to the previous literature (Han, 2021).

Case Study

Simulation Scenario Setup

The case takes place in a wide water area in the sea east of the Zhoushan Islands, located at approximately 123◦ W, 30.9◦ N. The specific initial-state settings of the ship are listed in Table 1.

Simulation Experiment and Results

To verify the reliability of collision avoidance decisions, a three-ship encounter scenario is selected in this case. Through the operation of the system platform, six end states are obtained, including five safety states and one collision state. Table 2 displays the simulation results of the system.

The experiment follows a pre-defined multi-vessel collision avoidance scenario for testing the reliability of ship collision avoidance decisions. All ships that participated in the experiment were designed to make risk decisions using a unified collision avoidance algorithm, specifically a multi-ship path planning algorithm based on the OIPD (Observation Inference Prediction Decision) decision framework (T. Wang et al., 2020).

In this experiment, the branch generation scan step for the DDET was set to 3 minutes in the scenario control module of the MADS-IDAC system. This means that after every 3 minute cycle of running the physical scenario, the system would check whether a new branch had been generated or not. Until the collision between the two ships 15 minutes later, a total of six end states had been generated.

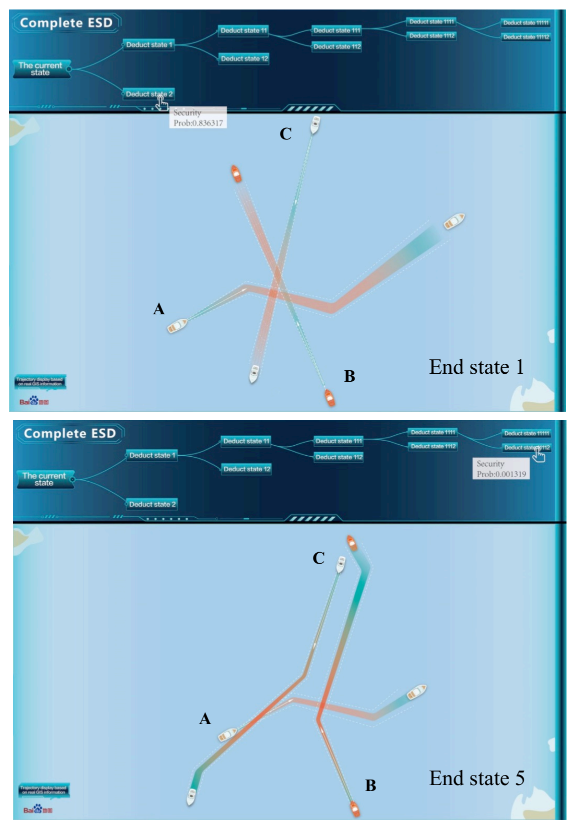

Figure 5: States 1 and 5 in the three-ship encounter simulation scenario

Among them, end states 1 to 5 successfully avoided a collision, attributed to timely collision-avoidance decisions. However, in the final state, due to the ship giving way not having enough time to make a collision-avoidance decision and maneuver, a ship collision accident occurred.

Based on the results of the system operation, it is apparent that states 1 and 5 have the largest difference in probability values in terms of safety results. The system retrieves the historical voyage trajectories of these two states, as shown in Figure 5. The Event Sequence Diagram (ESD) above marks the end state corresponding to the current scene. End state 1 is the deduced state 2 of the current event tree, with one levels of branching and a total collision avoidance time of 3 minutes. End state 5 is the deduced state 11112(presented in ESD) of the current event tree, with five levels of branching. The results of the historical navigational trajectory graphs indicate that there is still a chance of collision avoidance for the giving way vessel, even though there is already a high risk of collision at end state 5.

Actions and Decision-Making of the Crew On-Duty

According to the simulation results of MADS-IDAC platform, it can be concluded: The scenario in the end state 5 resulted in a 15-minute usage time for the entire collision avoidance due to the delay in decision-making. Fortunately, even with a probability of 0.001319, collision avoidance was still successful.

In this section, we analyze the actions and decision-making of the crew on-duty by using the end state 5 of a three-ship encounter collision avoidance scenario as an example. Figure 6 displays the significant branch points of the crew on-duty 's actions, as generated by the system. Based on the objectives and strategies generated by the system, the scenario is restored, depicting the course of the three-ship encounter that leads to the end state 5 of the collision avoidance scenario.

Case setting: The weather is clear with good visibility, northeast winds of force 2-3, and high tide.

Ship A: The ship is heading at 45° with an initial speed of 16 miles/hour. Two radars are in use.

At the 0th second, the radar detected the target ship, triggering an alarm. The crew on-duty selected LE as the problem-solving strategy, and subsequently determined the location of the target ship. At the 69th second, the ODM decided to communicate with ships B and C, and OPA was communicated to OSA for operation. However, neither of the target ships responded. After the crew on-duty changed tactics to W&M, the alarm sounded again. At the 702nd second, ODM decided to adjust the heading to 115° for avoidance action. Ship A continued to maintain speed and move forward. Subsequently, ship B turned to the right, and both ships A and B safely avoided the collision. After sailing to a safe distance, at 1349 seconds, ODM decided to adjust the sailing direction to 70 degrees (the ship turned left) and return to the original course. Ship A continued to maintain speed, direction, and observe the target ship. At the 1800th second, Ship A observed that ships B and C behind her had also successfully avoided the collision. Thus, the three-ship encounter scenario's collision avoidance was successful.

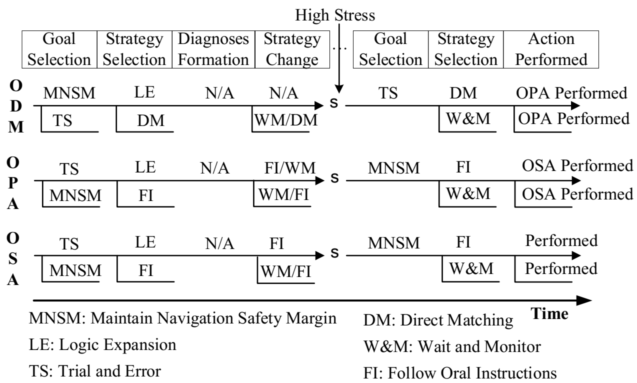

Figure 6: Major branch points of the crew on-duty's actions generated by the system

Table 3 displays a portion of the event timeline highlighting the decision changes made by the decision maker. This sequence presentation represents the crew on-duty's goals and strategies in solving the problem and the interactions between them, which are clearly recorded by the system.

Conclusion

Shipping safety is always a concern, with the status of the crew on-duty and timing of decision-making being key factors that affect the safety of ship navigation. However, the traditional static risk analysis method cannot fully address the deep mechanisms of maritime accidents. Therefore, this paper proposes the MADS-IDAC dynamic risk platform, which uses collision scenarios as an example to conduct simulation experiments and verify ship encounters. The platform simulates the development process of collision accidents under real risk scenarios, driven by a logical sequence of event development. By combining the behavior model of the crew on-duty with the ship control model, the human-machine interaction process, and the behavior of the ship in a real environment are simulated. This generates event tree branches dynamically to obtain event results and corresponding probabilities under risk scenarios. The model enriches the application range of the ADS-IDAC simulation model, and the case analysis proves that the decision-making process of the crew on-duty is affected by their cognitiv

Time (Sec.)	ODM Response	OPA Response	OSA Response	Ship Response
0				Alarms occur
1	Changes Goal to MNSM	Changes Goal to TS	Changes Goal to TS	
2	Changes Strategy to LE	Changes Strategy to LE	Changes Strategy to LE	
3	Check and locate	Check and locate	Check and locate	
68	Changes Strategy to DM	Changes Strategy to FI	Changes Strategy to FI	
69	Decision-making: Communicate with ship B, C	Decision-making: Communicate ship B, C		
70			Take action	
71			No reply	
196	Changes Strategy to W&M	Changes Strategy to W&M	Changes Strategy to W&M	
196-449	···Part of the information on crew and system activities is omitted to focus on key points···			
450				Alarms occur
601	Changes Sub-Goal to DAP	Changes Sub-Goal to DAP		
	Changes Goal to TS	Changes Goal to MNSM	Changes Goal to MNSM	
	Changes Strategy to DM	Changes Strategy to FI	Changes Strategy to FI	
702	Adjust course to 115°			Adjust course to 115°
703		Take action		
810	Changes Strategy to W&M	Changes Strategy to W&M	Changes Strategy to W&M	
811	Maintain speed and direction			
812-1347	···Part of the information on crew and system activities is omitted to focus on key points···			
1348	Changes Strategy to DM	Changes Strategy to FI	Changes Strategy to FI	
1349	Adjust course to 70°	Adjust course to 70°		Adjust course to 70°
1401			Take action	
1673	Maintain speed and direction Observation the ship B, C			
1674-1799	···Part of the information on crew and system activities is omitted to focus on key points···			
1800			Navigation safety Problem solving	

Table 3. Timeline of events in State 5

state. The feasibility of incorporating the IDAC model into the dynamic PRA simulation environment MADS is also demonstrated.

This study proposes a new approach to using quantitative dynamic risk analysis and human factor reliability analysis in high-risk, high-uncertainty environments with large degrees of freedom. Specifically, it focuses on heterogeneous traffic flows, which are mixed scenarios of manned and unmanned intelligent vessels. The proposed approach can facilitate better understanding of the working state of manned systems by intelligent systems, and enable a transformation from human-human to human-AI interaction.

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