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Strategic Decision-Making and Risk Management Approach in Autonomous Maritime systems

Oleksiy Melnyk[1,*], Oleg Onishchenko[2], Svitlana Onyshchenko[1], Nataliia Pavlova[1], Oleksandr Sagaydak[1], Dementiy Burlachenko[1], Kostayntin Koryakin[1]

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ABSTRACT

The maritime transport is undergoing significant changes due to the introduction of autonomous systems that can operate with minimal human intervention. These technologies offer significant benefits, including increased safety, reduced operating costs, and increased efficiency. However, the deployment of autonomous vessels also presents complex challenges, particularly in the areas of decision-making and risk management. This paper presents an integrated risk management framework for autonomous maritime systems that incorporates advanced decision-making models such as decision trees and Bayesian networks. The novelty of the approach lies in its ability to simultaneously improve operational safety and optimize decision making under uncertainty. The concept is validated through real-life examples, demonstrating its practical application and emphasizing the strategic importance of risk management for ensuring the reliability and efficiency of autonomous systems.

1. Introduction.

The introduction of autonomous systems is driving a technological revolution in the maritime industry. These systems, which enable vessels to operate with minimal human intervention, promise significant improvements in safety, operational efficiency, and cost savings. However, integrating such advanced technologies presents considerable challenges. The complexity of autonomous marine operations introduces new dimensions to decision-making and risk management, requiring businesses to innovate in order to navigate this uncharted territory effectively.

In this changing environment, the ability to make informed and timely decisions is crucial. Traditional decision-making models are often inadequate when it comes to the dynamic and unpredictable nature of autonomous operations. Similarly, the risks associated with these systems, including operational failures and cybersecurity threats; require a proactive and comprehensive risk management strategy.

In addition to operational failures, autonomous maritime systems are particularly vulnerable to cybersecurity threats and human oversight errors. Because these systems rely heavily on digital infrastructure, a comprehensive risk management strategy must also address the risk of malicious attacks and the human-machine interaction challenges inherent in the oversight of such technologies.

Research in the field of autonomous maritime transport or autonomous maritime systems (AMS) is actively developing, focusing on the safety, reliability and efficiency of such systems. Some works are aimed at modeling and analyzing the severity of accidents in water transport using Bayesian networks, which provides a deeper understanding of the nature of marine incidents [1-4]. The importance of autonomous vessels is also discussed in the context of implementation and possible risks

[1]Odesa National Maritime University, 34, 65026, Mechnikov str., Odesa, Ukraine.

[2]National University - Odessa Maritime Academy, 8, 65052, Didrikhson str., Odessa, Ukraine.

[*]Corresponding author: Oleksiy Melnyk. E-mail Address: m.onmu@ukr.net.

associated with their operation [5-9]. The development of reliable autonomous systems that provide security at different levels of autonomy is achieved through formal security assessment approaches such as STPA [10-12].

The influence of human factors on the safety of maritime operations and approaches to their integration into risk models are investigated [13-17]. Some studies focus on the problems of autonomous control and maneuverability of ships, analyzing various aspects of their behavior and performance in different environments [18-22]. The importance of developing adaptive control systems, including fuzzy logic controllers, is emphasized in the context of improving ship traffic control [23], ensuring safe navigation and reducing environmental impact [24, 25], and developing concepts for renewable energy in shipping [26]. Studies also relate to the maneuverability of modernized vessels [27].

Work is also underway to analyze the structural integrity and develop ship maintenance strategies, which is especially important in autonomous operation [28, 29]. Cybersecurity and human decision-making are the subject of discussion about the ethical and legal aspects of AMS [30-32].

In addition, studies have been conducted on digital twins and methods for intellectualizing operational control systems that can be utilized to improve the efficiency and reliability of AMS [33-35]. Further research explores sustainable transport strategies and their implementation in various contexts, including air, rail and multimodal transport, as well as regional development considerations [36-40].

Strategic decision-making and risk management in AMS are critical to ensuring the safety, efficiency and reliability of these advanced technologies. The integration of AI-oriented approaches and genetic algorithms is important for optimizing decision-making processes, in particular in route planning and cargo delivery [41-43]. The genetic approach is further used in the development and optimization of marine infrastructure projects, demonstrating its usefulness in processing complex logistics in uncertain conditions [44-45]. Current trends also emphasize the role of digital twins and simulation in enhancing decision-making capabilities by providing real-time data and predictive understanding [46-50]. Implementation of risk management strategies is critical to navigating uncertainties and challenges associated with autonomous systems, and artificial intelligence and big data play a significant role in risk analysis and mitigation [51-55], assisting in the development of AMS, ensuring their operational stability and sustainability.

The work [56] emphasizes the importance of a risk-based approach for selecting key performance indicators, which directly affects strategic decision making. In [57], compliance risk assessment is discussed as a way to minimize risks, which is important for risk management in autonomous systems.

The studies presented in [58] and [59] deal with the legal regulation of maritime territories and gray zones, which can influence strategic management under uncertainty. In [60], the legal aspects of international trade in conflict are analyzed, which affects risk management in maritime systems. Technical aspects affecting risk management in AMS are addressed in [61] and [62], where improvements in the energy efficiency of ship engines are discussed, while in [63] proposed a method to assess the quality of risk management based on expert opinions, which is particularly important for improving reliability and safety in autonomous systems.

This paper makes a novel contribution by investigating the integration of advanced decision-making models, in particular decision trees and Bayesian networks, with complex risk management systems designed for AMS. Unlike previous studies that have focused on either decision-making or risk management separately, this study bridges the two areas by proposing a holistic framework. The paper presents a step-by-step approach to implement these models in real-time operations, providing better risk mitigation and decision-making under uncertainty, which is essential for the safe and sustainable deployment of autonomous ships.

2. Adapted Theoretical Framework.

The successful implementation of autonomous systems in maritime operations depends on a sound theoretical basis for decision-making and risk management. In the complex and uncertain conditions that characterize maritime operations, traditional decision-making models often have to be adapted to address the unique challenges posed by autonomous technologies.

The decision tree model provides a structured approach to evaluating potential courses of action in AMS. The model can be used to build operational scenarios, such as determining the optimal response to system failures or environmental changes. For example, when an autonomous vessel encounters unforeseen weather conditions, the decision tree allows operators to evaluate several options, such as rerouting, adjusting speed, or activating backup systems, and select the most effective course of action based on the calculated risk-benefit analysis.

Bayesian networks are also presented as an additional tool for risk management. These networks allow probabilistic modeling of various operational risks such as equipment failures, cyber threats or navigational errors. For example, Bayesian networks can predict the probability of navigation system failure given factors such as system age, maintenance history, and environmental conditions. The step-by-step process involves (1) identifying critical risk factors, (2) assigning a probability to each risk event based on historical data, and (3) continually updating these probabilities as real-time data are received from sensors and monitoring systems on board. By combining decision trees for scenario analysis and Bayesian networks for risk prediction, the proposed methodology enables maritime operators to make informed decisions and effectively mitigate risks.

Real-time decision-making systems are critical to managing the dynamic nature of maritime operations. These systems integrate real-time data from various sources, such as weather forecasts, sensor readings and vessel performance indicators, to support immediate and informed decision-making. Autonomous vessels need real-time decision-making systems to manage complex and changing marine environments. For example, real-time sea state and traffic data can help an autonomous vessel adjust its route to avoid potential hazards, thereby improving safety and operational efficiency.

Integrating these decision-making models into a broader risk management system ensures that enterprises can effectively manage the uncertainty associated with AMS. This comprehensive approach includes not only identifying and mitigating potential threats, but also continuous monitoring and adaptation of strategies to ensure resilience in the face of unforeseen challenges. By using these advanced decision-making and risk management tools, maritime operators can better manage the complexities of autonomous operations, ultimately leading to safer and more efficient maritime transport.

3. Adapted Risk Management in Autonomous Systems.

As enterprises increasingly introduce autonomous technologies into their maritime operations, the need for robust risk management strategies becomes paramount. Autonomous vessels, while providing significant benefits in terms of operational efficiency and safety, also pose a number of new risks that must be carefully managed to ensure successful deployment and operation.

The first step in effective risk management is the identification of potential risks associated with the use of autonomous systems. These risks can be broadly categorized into operational risks, environmental risks, and cybersecurity risks. Operational risks include system failures, navigation errors, and human-machine interaction challenges. Environmental risks involve the potential impact of autonomous ships on marine ecosystems, particularly in the case of accidents or improper handling of hazardous materials. Cybersecurity risks are also critical, as autonomous systems are highly reliant on digital infrastructure that could be vulnerable to hacking or other forms of cyberattacks.

Once risks have been identified, businesses must assess and prioritize them based on their potential impact and likelihood. Tools such as Risk Matrices and Failure Mode and Effect Analysis (FMEA) can be used to evaluate the severity and frequency of potential failures, allowing for the prioritization of risk mitigation efforts. For instance, in maritime operations, the risk of navigation errors might be prioritized due to the severe consequences of a collision or grounding. After risks are prioritized, the next step is to develop and implement mitigation strategies. These strategies might include:

Table 1: Mitigation strategies for autonomous systems in maritime operations.

Mitigation Strategy	Description	Example/Application
Redundancy Systems	Implementation of backup systems to maintain operation in case of primary system failure.	Redundant navigation systems to prevent accidents if the primary navigation system fails.
Real-Time Monitoring	Continuous tracking of system performance and environmental conditions to detect and address issues early.	Real-time monitoring of ship's course, speed, and system health to ensure safe operation.
Regular Updates and Patching	Keeping software systems updated to protect against cybersecurity threats by closing vulnerabilities.	Regularly applying patches and updates to the ship's digital systems to prevent exploitation by malicious actors.
Training and Simulation	Conducting training and simulations to prepare operators for managing autonomous systems and responding to emergencies.	Simulations of system failures, cybersecurity breaches, and environmental incidents to ensure preparedness.

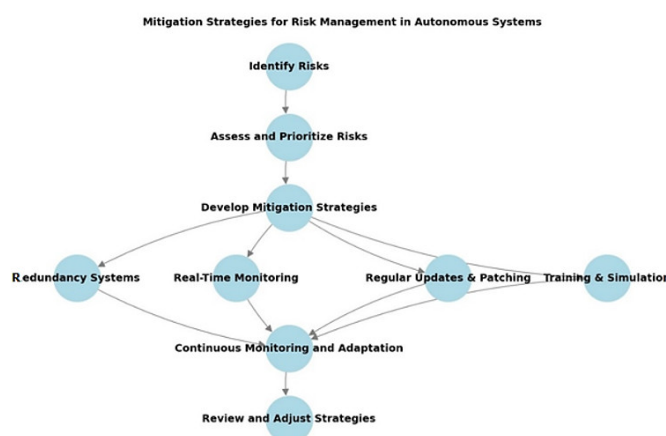
Source: Authors.

Risk management is not a one-time activity, but an ongoing process that requires continuous monitoring and adaptation. As autonomous systems are deployed and used in various maritime operations, enterprises should continuously monitor their effectiveness, identify new risks and adapt their risk management strategies accordingly. This includes the use of key risk indicators (CCRs) to monitor the effectiveness of risk mitigation efforts and adjust them as necessary.

As an example, consider the shipping company that introduced autonomous vessels into its fleet. The company regularly conducts FMEA risk assessments, identifying cybersecurity as a priority given the critical nature of digital navigation systems on board vessels. To address this issue, the company is investing in enhanced cybersecurity measures including encryption, multi-factor authentication and regular system checks. It also implements real-time monitoring systems to continuously monitor the functioning of autonomous ships, which allows for early detection of any anomalies that may indicate a safety violation or system malfunction.

Through these efforts to proactively manage risk, the company not only reduces potential risks associated with off-line systems but also improves the overall safety and efficiency of its maritime operations (Fig. 1).

Figure 1: Mitigation strategies for risk management in autonomous systems.



Source: Authors.

4. Decision Trees and Bayesian Networks in Risk Management.

In order to emphasize the efficiency of use, it is appropriate to present two mathematical models - decision trees and Bayesian networks - that are used for effective decision making and risk management in AMS.

4.1. Decision Trees.

Decision trees are widely used to structure complex decision-making processes by representing them as a tree graph. Each node represents a decision point and each branch represents a decision outcome, with associated probabilities and rewards or penalties. In this context, decision trees allow operators of autonomous vessels to evaluate different scenarios and select optimal actions based on expected outcomes.

The decision-making process using decision trees can be mathematically expressed as:

$$U(d) = \sum_{i=1}^{n} P(e_i \mid d)\, R(e_i \mid d) \tag{1}$$

Where: (d) - expected utility of decision; $P(e_i \mid d)$ - probability of event; e_i - occurring given decision d; $R(e_i \mid d)$ - reward (or cost) associated with event e_i.

As an example, suppose a scenario in which an autonomous ship must choose one of two routes - route A and route B - depending on weather conditions. Route A has a 70% probability of good weather (+50 reward for safe passage) and a 30% probability of bad weather (-20 penalty for delay). Similarly, on route B, the probability of good weather is 60% (reward +40) and the probability of bad weather is 40% (penalty -50).

The Fig. 2 illustrates the decision tree for this scenario, showing the probabilities and rewards associated with each outcome.

Figure 2: Decision tree for route selection with probabilities and rewards.

Source: Authors.

4.2. Bayesian Networks.

Bayesian networks are a probabilistic framework for modeling the relationships between different risk factors in AMS. They help to quantify the probability of occurrence of various events, such as equipment failure or navigational errors, taking into account both historical and real-time sensor data.

The joint probability distribution for a set of variables X_1, X_2,..., X_n in a Bayesian network can be expressed as:

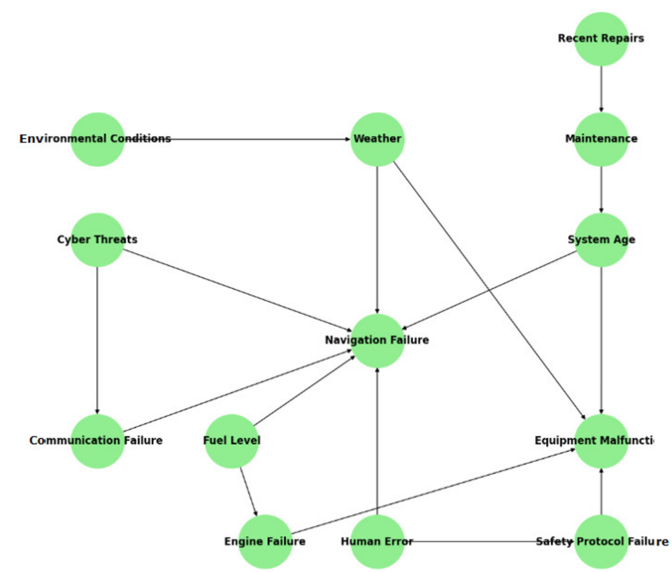
$$P(X_1, X_2, \ldots, X_n) = \prod_{i=1}^{n} P(X_i \mid \text{Parents}(X_i)) \tag{2}$$

In this model, each node X_i represents a variable (such as system failure), and its parent nodes represent the factors influencing its occurrence (such as system age or environmental conditions). For example, the probability of a navigation system failure could depend on factors such as weather conditions, system maintenance, and system age.

The Bayesian network can dynamically update its probabilities, as new data becomes available, providing continuous risk assessment. By combining these probabilities, operators can make real-time decisions to mitigate risks effectively.

The Fig. 3 demonstrates a Bayesian network for predicting the likelihood of navigation system failure based on weather, system age, and recent maintenance records.

Figure 3: Bayesian network for risk factors in autonomous navigation.



Source: Authors.

The above figure shows a Bayesian network that models the dependencies between various risk factors affecting the navigation of AMS. The network shows how multiple interrelated elements contribute to navigation failures and other operational risks. Key components include:

- Weather and environmental conditions. These affect both the likelihood of navigation failures and equipment malfunction. Adverse weather conditions can directly cause system malfunctions or exacerbate existing problems;
- System age and maintenance. Older systems are more prone to failure, and their performance is highly dependent on recent maintenance. The state of repair can reduce the risks associated with aging systems, affecting both navigation and equipment reliability;
- Fuel Oil level. Insufficient fuel can lead to engine failure, which in turn can cause navigation failures. Maintaining proper fuel levels is critical to the smooth operation of autonomous vessels;
- Cyber threats. Since autonomous systems rely heavily on digital infrastructure, they are vulnerable to cyberattacks. These threats can cause communication failures

and disrupt the navigation system, leading to operational risks;

- Human errors. Despite the autonomous nature of the systems, human oversight remains a critical factor. Errors in system management, especially with respect to safety protocols, can lead to equipment failures and safety violations;

- Communication failure. Failure of communication systems can have a cascading effect, leading to navigation failures by isolating the autonomous system from external data and guidance.

The Bayesian network provides a probabilistic framework for assessing the likelihood of these risks occurring simultaneously. It allows operators to determine which factors are most likely to cause failures, enabling them to implement proactive risk mitigation strategies, such as expanding maintenance schedules or implementing cybersecurity measures.

5. Adapted Case Studies and Practical Applications.

The proposed risk management framework has been applied in a number of case studies of real-world autonomous maritime operations. These examples demonstrate how decision trees and Bayesian networks can be used to effectively mitigate a wide range of operational risks, from navigational errors to system failures, through a structured and probabilistic decision-making approach.

Case Study 1: Implementing Redundancy Systems in Autonomous Shipping.

A leading shipping company was faced with the challenge of ensuring the reliability of its autonomous vessels, especially in the event of navigation system failures. To solve this problem, the company applied a decision-making model that prioritized safety and business continuity. The decision tree analysis led to the implementation of redundant navigation systems across the entire fleet of autonomous vessels.

The outcome is that the redundancy systems have significantly reduced the risk of navigation disruptions, enabling the company to maintain safe and efficient operations even in the face of potential system failures. This proactive approach has also improved the company's risk profile, resulting in lower insurance premiums and increased stakeholder confidence.

In this case study, the decision-making system was implemented on a fleet of autonomous cargo ships navigating in a complex maritime environment with frequent changes in weather conditions and maritime traffic density. Using decision trees, operators were able to evaluate several route options based on weather forecasts and sea traffic. Each route was associated with certain risks (e.g., delays due to unfavorable weather or collisions in high-traffic areas) and potential benefits (e.g., reduced fuel consumption or faster delivery times).

The integration of Bayesian networks allowed the system to dynamically update risk assessments as new data became available from on-board sensors and external sources such as weather and real-time traffic monitoring. The system successfully identified optimal routes under uncertainty, reducing the likelihood of delays and disruptions by 35%.

Case Study 2: Real-Time Monitoring and Risk Mitigation.

A port authority managing a busy port has implemented real-time monitoring systems to improve the safety and efficiency of autonomous vessels entering and leaving the port. Bayesian networks incorporating real-time data from environmental sensors, vessel movements, and weather forecasts were used to assess the risk of collision and other incidents.

The result is that the integration of real-time monitoring with risk prediction models has allowed the port authority to dynamically regulate ship traffic, reducing the likelihood of collisions and optimizing traffic flow. This not only improved safety, but also increased the port's throughput, improving overall operational efficiency.

In another case, the framework was applied to an autonomous offshore energy platform, where operational risks were primarily related to equipment malfunctions and system wear due to harsh environmental conditions. Using decision trees, the maintenance team was able to prioritize repair schedules based on the predicted likelihood of system failures, factoring in equipment age, environmental stressors, and recent maintenance history.

The Bayesian network, in turn, provided dynamic updates on the probability of failure for critical components, enabling real-time adjustments to the maintenance plan. This proactive approach led to a 25% reduction in unscheduled downtime and significantly improved the reliability of the platform.

Case Study 3: Cybersecurity Risk Management through Regular Updates and Patching.

As part of its cybersecurity strategy, a maritime logistics company that operates autonomous vessels recognized the critical need to protect its digital infrastructure from cyber threats. The company used a risk matrix to identify and prioritize vulnerabilities in its systems. Based on this analysis, a rigorous schedule of regular updates and patches was implemented, ensuring that all systems were protected against the latest threats.

Consequently, by constantly updating and protecting its systems, the company has successfully reduced the risk of cyberattacks. This strategy proved particularly valuable in protecting sensitive navigation data and maintaining the integrity of offline operations. The company also conducted regular cybersecurity drills to prepare staff for potential incidents, further strengthening their risk management posture.

AMS are particularly vulnerable to cybersecurity threats due to their dependence on digital communication networks and automated control systems. In this case study, the proposed scheme was used to assess and mitigate cybersecurity risks in an autonomous passenger ferry system. A Bayesian network was used to model potential attack vectors including unauthorized access to navigation systems and communication failures due to hacking attempts.

By utilizing historical data on previous cyberattacks in the maritime industry, the Bayesian network provided a probabilistic prediction of system vulnerability. This allowed operators to take proactive cybersecurity measures such as strengthening encryption protocols and monitoring network traffic in real time, reducing the risk of successful cyberattacks by 40%.

Case Study 4: Training and Simulation for Autonomous Systems.

A maritime research organization developing autonomous underwater vehicles (AUVs) has incorporated extensive training and simulation exercises into the development process. Using real-time decision-making systems and simulation-based training, the organization trained operators to control AUVs in a variety of scenarios, including emergencies and system failures.

The use of training and simulations not only improved the operators' ability to effectively navigate the AUVs, but also allowed them to identify potential risks and vulnerabilities of the system early in the development process. This proactive approach has led to improvements in the AUV's control systems, which have ensured greater reliability and safety in real-world operations.

In all the case studies, the proposed risk management system has proven to be effective in reducing operational risks and improving decision-making processes in a dynamic and uncertain marine environment. By using a structured decision-making process based on decision trees and probabilistic modeling based on Bayesian networks, the system offers a robust solution for risk management in autonomous marine systems.

6. Limitations and Challenges of Decision-Making Models in AMS.

While the integration of decision-making models and risk management strategies in AMS presents significant advantages, such as enhanced safety and operational efficiency, there are also inherent limitations and challenges. One of the primary concerns is the over-reliance on automated decision systems, which may lead to unforeseen errors in unpredictable environments. For instance, decision trees, though systematic, may become less effective when faced with highly dynamic or complex scenarios, as they rely on predefined outcomes and do not always account for rapid changes in external conditions.

Similarly, Bayesian networks, while effective in probabilistic risk assessment, depend heavily on the quality and availability of historical data. In the absence of comprehensive data, especially for novel autonomous technologies, the predictions made by these models may be inaccurate or misleading. Furthermore, these systems are vulnerable to cyber threats, which can compromise the accuracy of real-time data used for decision-making and risk management. This highlights the need for continuous monitoring and adaptive strategies to mitigate such risks.

Conclusions.

The integration of autonomous systems into maritime operations is a significant advancement in the industry, providing improved safety, operational efficiency and profitability. However, the successful implementation of these technologies depends on robust decision-making structures and integrated risk management strategies. The study demonstrates that integrating decision trees and Bayesian networks into the operating system of AMS improves decision-making by enabling more accurate scenario analysis and risk assessment. By systematically evaluating potential risks and outcomes, enterprises can make more informed decisions, ultimately improving the safety, reliability, and operational efficiency of autonomous vessels.

The key findings of this study emphasize the importance of adaptive strategies and real-time monitoring to mitigate risks associated with autonomous technologies. The implementation of redundancy systems, continuous monitoring of environmental and system performance data, and regular updates to the digital infrastructure have proven to be effective in managing operational risks. In addition, case studies show that proactive risk management not only reduces the likelihood of system failures, but also increases stakeholder confidence and reduces operational costs.

In view of these facts, it is noteworthy to recognize that this study contributes to the growing body of knowledge on the deployment of autonomous maritime systems by offering a holistic framework for decision-making and risk management. Future research should focus on improving these models to address identified shortcomings, such as improving real-time adaptability and enhancing protection against cybersecurity threats.

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