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Enhancing Ship Safety During Mooring Operations on The Basis of Expanded Parameters and Leveraging AI for Real-Time Risk Assessment

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ABSTRACT

This paper presents an innovative approach to improve the safety of ship mooring operations by applying an advanced risk assessment model that utilizes Bayesian networks and real-time data processing. The proposed system expands the number of risk parameters considered, including wind speed, current speed and crew fatigue, and utilizes artificial intelligence (AI) to dynamically update risk levels. The system is an end-to-end solution that integrates multiple data sources to provide continuous risk monitoring, reduce human error and improve decision-making during mooring operations. Case studies demonstrate significant reductions in critical incidents and overall operational risk.

1. Introduction.

Ship operations such as mooring are a significant risk due to the increasing complexity of shipboard systems and the human factor associated with manual risk assessment. Traditional mooring risk assessment methods rely heavily on static checklists and manual assessments, which are often subject to human error, especially in dynamic and unpredictable maritime environments. The proposed approach utilizes AI and Bayesian networks to create a flexible and adaptive risk management system that can accommodate changes in environmental conditions and vessel state in real time. By integrating more risk factors, the system aims to offer a more accurate and comprehensive assessment of potential hazards during mooring operations.

Safety management during mooring operations is an important task that requires a combination of standards, practical approaches and modern technologies. In the context of this study, various aspects aimed at improving safety and reducing risks during mooring operations are considered.

There are several approaches to risk management in mooring operations and one of the fundamental tools are the ISO 31000 and IEC 31010 standards. These standards provide guidance on general risk management and assessment methods, which makes them useful for analyzing and minimizing the hazards associated with mooring operations [1, 2]. The use of risk acceptance criteria, such as ALARP, plays an important role in this process, which help to determine which risks can be tolerated and which need to be eliminated. These methodologies enable a detailed approach to safety and more informed accident prevention strategies [3].

Practical use of risk management approaches is also confirmed by recommendations of professional organizations and experience in some ports. For example, Shipowners' Club provides recommendations for assessing and minimizing risks associated with mooring operations, which demonstrates the need for hybrid methodologies and integration of digital technologies [4]. The Port of Rotterdam's experience in using technologies such as digital call optimization in the port highlights the impor-

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tance of modern solutions to improve safety [5]. This approach optimizes operations and reduces the likelihood of incidents by analyzing real-time data and applying preventive measures.

In addition, research and security management models related to port operations emphasize the need for an integrated approach to risk assessment. Examples include resource efficiency analysis, risk modeling for port infrastructure facilities, and better prediction of hazardous situations such as accidents or collisions [6-9]. The use of hybrid analysis techniques, such as Fuzzy Fault Tree Analysis, not only allows for more accurate risk assessment, but also the development of specific risk prevention measures [10].

The complexity of day-to-day ship operations also plays a major role in safety management. For example, Functional Resonance Modeling allows the consideration of numerous factors that can affect the safety of a ship during mooring [13]. In this regard, safety management standards of various shipping companies are useful as they help to implement systematic approaches to risk mitigation [14-18]. At the same time, the importance of climatic factors should also not be underestimated as weather conditions can threaten the safety of mooring operations [19].

Currently, one of the most promising technologies for risk management is artificial intelligence (AI). The application of AI for analyzing data and predicting potentially hazardous situations is already being actively developed. The use of Bayesian networks and other machine learning models makes it possible to automate the processes of risk assessment and management, which is especially important when working in high-risk environments [24]. Modern risk modeling techniques, such as simulation modeling and evasion algorithms, help the crew to make decisions that are more informed and reduce the probability of accidents [31-32].

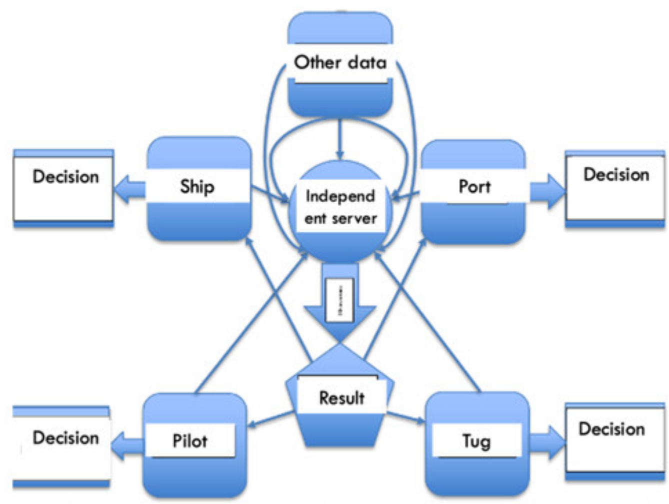
Thus, the literature review shows that the integration of standards, practice guidelines, advanced parameters and advanced technologies is required to ensure safe mooring operations. The application of AI, hybrid methods of risk assessment and modeling opens new opportunities for improving the accuracy of predictions and more effective safety management.

The purpose of this research is to develop and validate an improved risk assessment system that improves the safety of ship mooring operations by incorporating expanded risk parameters and using artificial intelligence for real-time analysis. Therefore, this research aims to reduce human error, improve the efficiency of risk assessment and provide dynamic data update throughout the mooring process, ensuring safer and more reliable operations.

2. Materials and Methods.

One of the advantages of round-circle risk assessment of operation is possibility to check much more risk parameters, than it could be done during routing risk assessment on board of the ship. Usually, risk assessment is done by simple tickling the boxes in the paper or electronic check-list. In both cases it is done manually, which is highly increases the human element influence. Taking into account overload of the modern ship's crew (due to constant shortening of crew complement and increasing of the volume of paperwork), limited time for risk assessment (there is no special time in the ship's schedule, dedicated to risk assessment, it should be done at the same time with main operations) and crew fatigue after sea passage, we can say that human error under the such circumstances is very probable. Concept of round-circle risk assessment can mitigate such risk. It is based on the main element – independent server, which collects data from all stakeholders and process them according to some certain algorithm (Fig. 1).

Figure 1: Scheme of the concept of round-circle risk assessment.



Source: Authors.

The main advantage of such model is use of modern IT technologies, which will allow to process much more data, then human can do, also – server can process all data (even changeable) in the real time mode. The process of the data transfer goes on separately for those data, which needs operator's assistance, data from ship's computer and live data from ship's mechanisms and devises. Thus, we have the opportunity to have live risk assessment during the whole time of the operation (Fig.2).

On the Figure 3 shown the possible algorithm of various data processing. They are divided by type and divided in time as well: some are processed before the operation, but some data to be processed continuously during operation.

As it was mentioned above, there are four stakeholders taking part in the mooring operation. Consider the stakeholder "Ship" as an example. It seems impossible to assess all risks might arise before and during operation with just only one method. Risk parameters and proposed methods of assessment them we grouped in the Table 1.

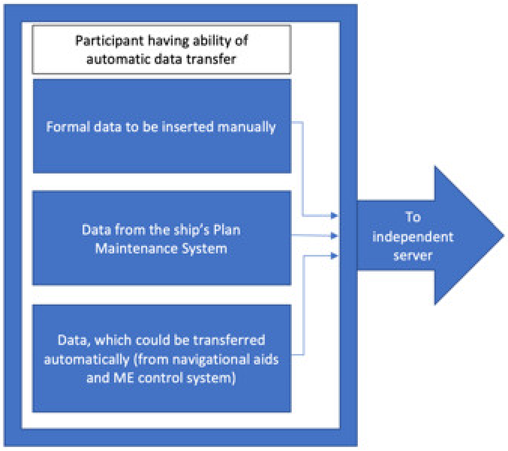
In the first group, the parameters may depend on other factors. For example, the actual condition of a vessel depends not only on its age, but also on its type, which should be taken into account. In addition, reliable data based only on the ship's age may not be sufficient for statistical analysis, as its condition is significantly affected by proper maintenance (the rating of the

Table 1: Expanded risk parameters and proposed methods of assessment.

Group of parameters	Risk parameter	Method of assessment
I group (unchangeable parameters)	Year of built of the ship	Expert assessment
	Type of the ship	Expert assessment
	Name of the Shipping Company (Ship's Manager)	Expert assessment
	Flag of the ship	Ratings
	Classification Society	Ratings
II group (depends on Ship/Company)	Number of non-conformities by PSC	Statistical analysis
	Number of detentions by PSC	Statistical analysis
	Number, type and level of accidents, the ship was involved	Statistical analysis
	If the ship participates in the Green Award programme or similar	Statistical analysis
III group (Ship's docs)	If all ship's documents are available	Statistical analysis
	If ship's documents are valid	Statistical analysis
	If some of the documents is not valid – analysis of the type of document and reason of invalidity	Statistical analysis
IV group (crew documents)	If crew complement is in order according to the Minimum Safe Manning Certificate	Statistical analysis
	If crew STCW documents all are valid	Statistical analysis
	If all crew STCW documents are verified, verification based on access to national verification system of the particular seafarer	Statistical analysis
	Experience of the seafarers – total sea service of each seafarer and his sea service on the particular type of the ship	Statistical analysis
	Age of the seafarers	Statistical analysis
V group (Ship's SMS)	How many nonconformities issued	Statistical analysis
	How many of them connected to the mooring operations/equipment	Statistical analysis
	How many accidents connected to mooring operations/equipment happened	Statistical analysis
	If there were repeated accidents	Statistical analysis
	How many near miss cases, connected to mooring operations/equipment found	Statistical analysis
VI group (Ship's equipment)	Number of navigational aids on board – is there sufficient number or redundant number of navigational aids	Statistical analysis
	Manufacturers of navigational aids (their rating in the industry)	Ratings
	Is there sufficient number or redundant number of auxiliary engines and how many are in operation	Statistical analysis
	Number of mooring aids	Statistical analysis
	Number of thrusters	Statistical analysis
VII group (Ship's PMS)	Was maintenance and check of the mooring equipment done as per plan	Events Tree Analysis
	Were spare parts requested for mooring equipment delivered and installed	Events Tree Analysis
	Were mooring ropes changed/checked according to schedule	Events Tree Analysis
VIII group (variable parameters)	Working parameters of ship's main engine – if there any malfunction, tendency to change to dangerous level	Bayesian networks or Markov chains
	Working parameters of steering gear – if there any malfunction, tendency to change to dangerous level	Bayesian networks or Markov chains
	Working parameters of auxiliary engines – if there any malfunction, tendency to change to dangerous level	Bayesian networks or Markov chains
	Navigational parameters – if any tendencies to run aground, if any risk to run against navigational obstacle, if any risk of collision	Bayesian networks or Markov chains
	Parameters of inertial navigation system	Bayesian networks or Markov chains
IX group (weather conditions)	Weather shore station and ship's meteorological station – if any tendency to worsen	Bayesian networks or Markov chains
	Light conditions – from light sensors	Bayesian networks or Markov chains
X group (cybersecurity data)	Data exchange with the ship in order to find potential risk of interference into the system	Bayesian networks
	Continuous ship's system checks on the matter of optimal performance	Bayesian networks

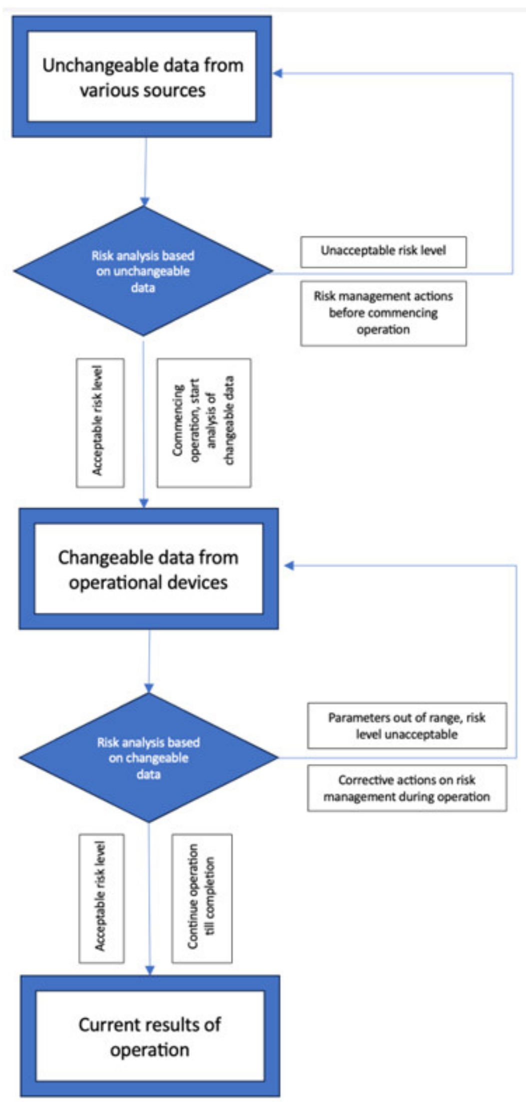
Source: Authors.

Figure 2: Three types of data, generated by Participant (stakeholder).



Source: Authors.

Figure 3: Data processing algorithm.



Source: Authors.

shipping company may be a valuable factor). These limitations can be addressed by using expert judgment methods, but this approach requires a significant number of experts to obtain accurate data.

Different flag states and classification societies have different safety requirements. Their ratings (e.g., PSC, P&I, or MoU, all of which provide ratings for flags and classification societies) can be used to evaluate them. To perform the statistical analysis, the necessary data must be collected from various sources such as PSC, MoU, GISIS, Equasis, etc.

The data sources for the first and second groups can be easily identified using artificial intelligence. In this study, several AI tools were tested and the best results were achieved using Perplexity. It is important to emphasize that AI should be used to find data sources and not to collect the data itself.

When conducting statistical analysis of parameters of the fifth group, Henry's law should be taken into account. The most important aspect of this approach is the inclusion of data variables - information that changes during operation in the list of estimated parameters.

Advances in information technology make it possible to analyze such data in real time, making it possible to predict possible mechanical failures or dangerous changes in the situation.

Every of these ten groups, even every risk parameter needs specific approach to calculate probability of the negative event. There are various methods to be used for that. The task for designers of the risk management system is to choose the most suitable method for every parameter. In reality it could be adjusted after practical implementation of first version of the risk monitoring internet platform.

The methodology of this study is based on the collection, categorization, and real-time analysis of both static and dynamic risk factors involved in ship mooring operations. The static risk factors include environmental conditions (e.g., wind speed, water currents), ship-specific characteristics (e.g., size, type, mooring equipment), and port infrastructure (e.g., dock configuration, available support). Dynamic risk factors, such as crew fatigue, real-time changes in weather, and ship movement, are continuously monitored using IoT sensors and integrated into the risk assessment system. The round-circle risk assessment concept leverages AI to process this data, allowing for real-time updates and adjustments to the risk profile.

The risk assessment model employs a weighted approach to aggregate the probabilities of individual risk factors, with each parameter's weight reflecting its relative importance based on historical incident data and expert judgment. The Bayesian network is used to continuously update these probabilities as new data becomes available. Additionally, a calibration process is implemented to refine the model's accuracy by comparing real-time risk predictions with historical data on past mooring incidents.

The system architecture consists of three layers:

- Data collection layer i.e. data from onboard sensors, port systems, and external databases (e.g., weather forecasts) are collected and transmitted in real-time;

- AI analysis layer while AI algorithms process the data to identify patterns, predict potential hazards, and calculate risk levels;

- Decision support layer where the processed risk information is displayed to the crew via a user-friendly interface, providing actionable insights and recommendations for mitigating risks during mooring operations.

It seems feasible after some certain time of testing such system, to make Pareto analysis in order to find those 20% (or a bit more) risk parameters, which may lead to accident during mooring operations. This to be done to facilitate work of the system and not to overload it.

During this research, we tested and analyzed various Artificial Intelligence tools, in order to find if they are applicable to round-circle risk assessment concept. The results are in Table 2.

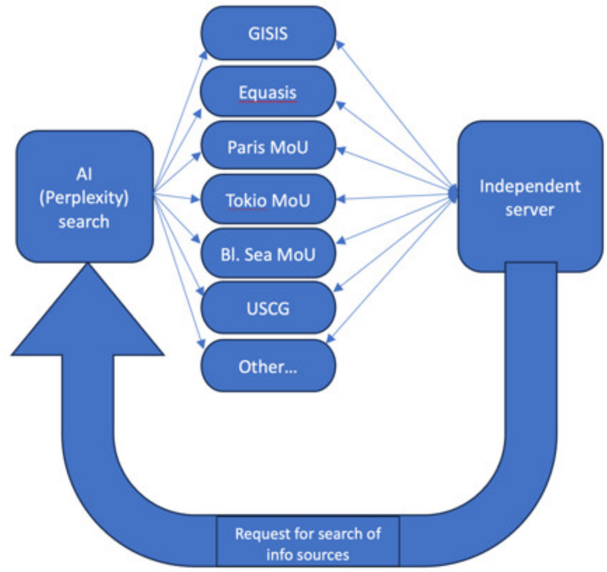
Table 2: Various artificial intelligence tools analysis for round-circle risk assessment suitability.

AI name	Applicability for the round-circle risk assessment
Microsoft Azure	Platform, which could be used for placing the system
TensorFlow	Limited application for our purposes
OpenAI (includes ChatGPT)	Very limited abilities, high probability of errors
Google AI Platform	High opportunities, however, prospects of use for our purposes are not so clear
Amazon Web Services	Platform, which could be used for placing the system
NVIDIA Deep Learning AI Software	Not suitable
Dataiku	Could be used for our purposes
H2O.ai	Could be used for calculation and analysis of data, might be used for our purposes
Rainbird	Not suitable
Caffe	Not suitable
Perplexity	Suitable as a search engine

Source: Authors.

Basing on the characteristics of the platforms, it is possible to say that several platforms might be used for placing of the risk-assessment system. It might be more feasible, than ordinary server. However, it is necessary to realize that for full-scale tasks of the system, AI tool should be properly trained, otherwise many errors can happen. The only purpose, which could be fulfilled by AI for the moment – searching the sources of information. The best results were achieved with Proplexity. It is necessary to stress: searching of particular data is not guaranteed (for example: statistics of accidents with particular ship – results not be found or found erroneous data), but searching for the sources gives quite good result. Basing on such results, system can obtain proper data using the ordinary search machine.

Figure 4: Scheme of using AI assistance for searching of the sources of information.



Source: Authors.

Comments to the scheme: the main server of the System makes a request to AI platform to find necessary sources of information (number of deficiencies, accidents, detentions, rating of the ship, etc.) about particular ship (and Ship's Operator). AI founds names of the organizations with their web-addresses. Having this information, Independent Server makes exact requests for particular data, using ordinary search engines, and obtains proper data.

Another task could be fulfilled by proposed conceptual internet platform – searching for the gaps, which may lead to Swiss cheese effect. System will trace possible consequences of bad events and found probability of trapping from one gap (if some negative event happened) into the next gap during mooring operation (Fault Tree Analysis). Of course, this is real time mode process.

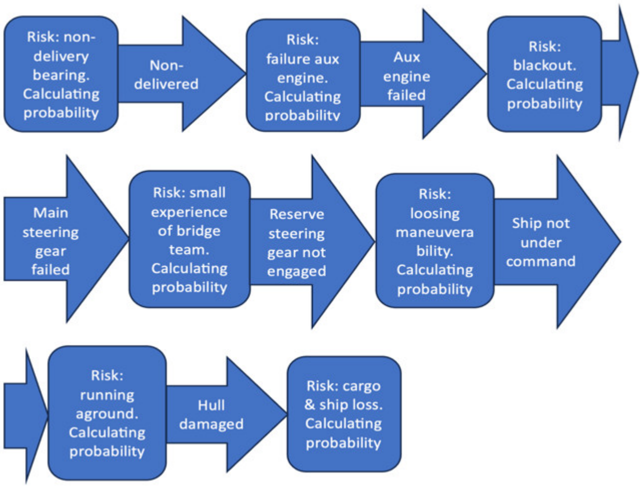
Example of such analysis given at Fig. 5. The situation: support bearing of auxiliary engine needs to be replaced. Request is placed at ship's Plan Maintenance System (connected to the Independent Server).

In order to simplify the picture just negative events are shown. The server analyzes possible chain of events, which may lead to accident or catastrophe. If probability of chain events would be higher than certain level (fixed by Company or P&I Club), the server will generate signal.

3. Results and Discussion.

In light of the above, we can propose an algorithm to improve the safety of ship mooring using artificial intelligence (AI) and risk assessment, which is based on a method of dynamic risk assessment based on sensor data updated in real time and a probabilistic model for predicting potential risks. The main steps of this algorithm can be mathematically formalized as follows:

Figure 5: Example of analysis of "Swiss cheese" events possibility.



Source: Authors.

1. Data acquisition from various sensors such as wind sensors, current sensors, ship position, data on port features, berth etc. are used. These will be the input parameters for the system. Let $X = x_1, x_2,..., x_n\}$ be a set of sensor data, where x_i is an individual measured parameter (e.g., wind speed, water depth, vessel position, etc.).
2. Risk probability calculation, for which Bayesian networks used, for example, to predict the probability of risk events based on current data:

$$P(R \mid X) = \frac{P(X \mid R)\, P(R)}{P(X)} \tag{1}$$

where: $P(X \mid R)$ - probability of observing the data X in the presence of risk R, $P(R)$ - a priori probability of the risk, $P(X)$ - full probability of the data.
3. Multi-parameter risk assessment where a multi-criteria decision making model is applied, where each risk is assigned a certain weighted probability depending on the criticality of the parameter;

$$R_{\text{total}} = \sum_{i=1}^{n} w_i \cdot P(R_i \mid X) \tag{2}$$

where: $P(R_i \mid X)$ - probability of a particular risk R_i based on the data X, and w_i - risk weight.
4. Decision-making, which is based on the current risk level and decisions are made to adjust the mooring process. If R_{total} exceeds a certain threshold λ, the system may suggest correcting the mooring operation.

The proposed algorithm, with the necessary elements to be applied in real conditions for risk management during ship mooring, is used:

Step 1: Data collection and preprocessing. Input data set $X = \{x_1, x_2, \ldots, x_n\}$ includes indicators that affect the mooring process. For example: x_1- wind speed, x_2 - force of the current, x_3 - condition of mooring ropes, x_4 - vessel loading status, x_5 - distance to the pier, x_6 - data on crew actions (e.g., fatigue, error), x_7 – ship speed, etc. Each parameter is read in real time by sensors and fed into the risk management system.

Step 2: Calculating the underlying risk probability. Each risk factor corresponds to a risk probability $P(R_i \mid X)$, where R_i - specific risk event (e.g., loss of ship control). A Bayesian network used to account for the relationships between parameters.

Let us consider three main parameters x_1 (wind speed), x_2 (current force), and x_5 (distance to the pier). Risk event R_1 (loss of control) can be described by a probabilistic dependence on these parameters:

$$P(R_1 \mid x_1, x_2, x_5) = P(x_1 \mid R_1)\cdot P(x_2 \mid R_1)\cdot P(x_5 \mid R_1)\cdot P(R_1) \tag{3}$$

where: $P(x_1 \mid R_1)$ - probability of high wind speed when control is lost, $P(x_2 \mid R_1)$ - probability of a strong current, $P(x_5 \mid R_1)$ - probability that the vessel is at an unsafe distance from the pier.

Step 3: Weighted sum of risks. Once calculated the probability of each risk event, we can use the weighted sum to estimate the total risk:

$$R_{\text{total}} = \sum_{i=1}^{n} w_i \cdot P(R_i \mid X) \tag{4}$$

Here w_i - the weight of each risk factor, which is given by experts based on its importance in the mooring conditions. As example for (R_1), (loss of ship control) weight w_1 may be higher than for other risks such as mooring failures R_2.

Step 4: Dynamic Risk Update. The system uses IoT sensors to collect data in real time. Every time a new value is received X, the Bayesian network recalculates the probabilities and updates the overall risk score R_{total}. As example if a sudden increase in wind speed x_1 is reported, the system recalculates $(R_1 \mid x_{1,2}, x_5))$, which may result in an increase in the overall risk score.

Step 5: Decision Making. After updating the overall risk R_{total}, the system checks if the risk exceeds a given threshold λ. If $R_{total} > \lambda$, then the system generates a warning to the crew to correct actions. This may include:

- Correcting the speed of the vessel;
- Course changes;
- Increased control of mooring ropes;
- Use of tugs for stabilization.

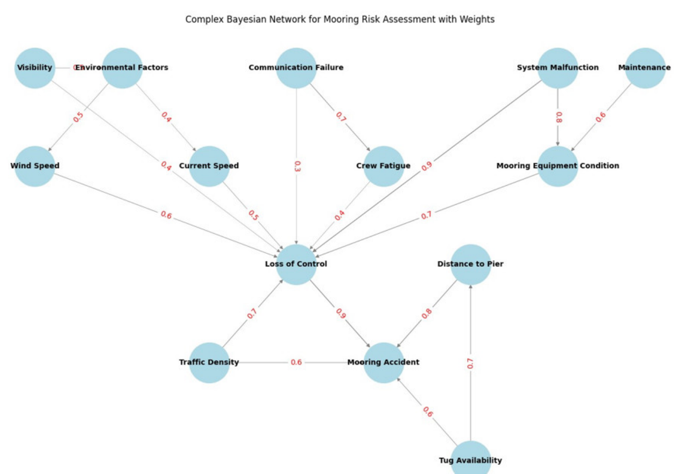
Step 6: Optimize risks with AI where can be used to predict potential scenarios based on current data and historical risk data. The system can suggest optimal actions depending on the situation. For example, if there is an increased risk of loss of steering due to strong winds and currents, the AI can suggest the use of additional tugs to support the vessel. The solution D can be chosen based on minimizing the total risk:

$$D = \arg\min_{d \in D}(R_{\text{total}}(d)) \tag{5}$$

Where d are the different possible actions (e.g. speed change, use of tugs), and the action that minimizes the overall risk score is selected.

The graph on Figure 6 represents a Bayesian network for assessing risks during the ship mooring. The nodes represent risk factors and events (e.g. wind speed, crew fatigue, loss of control) and the edges represent their relationships. The weights on the edges show the degree of influence of one factor on another, reflecting the probabilities of different scenarios. This model allows for accurate risk assessment and dynamically updated predictions based on real data, which improves mooring safety.

Figure 6: Bayesian network for risk assessment of ship mooring risks.

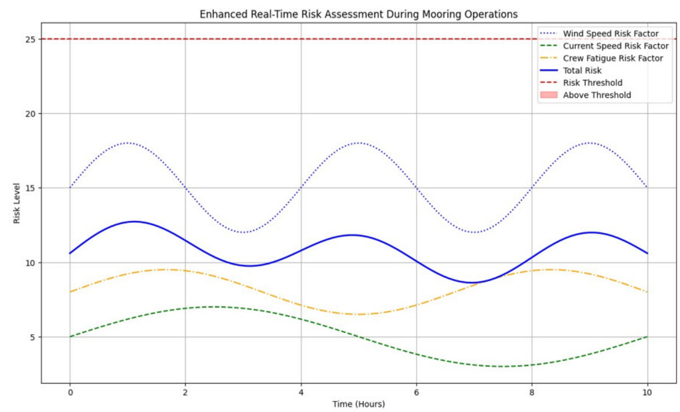


Source: Authors.

The graph on Fig. 7 shows a real-time assessment of the risk of mooring a vessel taking into account several factors: wind speed, current strength and crew fatigue. The lines show the contribution of each risk factor and the final "Total Risk" line represents the total risk level calculated based on all parameters. The red dashed line indicates the threshold at which risk becomes critical. Areas where the risk exceeds the threshold are highlighted in red and "High Risk" annotations indicate periods of high risk. This graph allows to visualize how different parameters affect the overall risk and helps to make more informed decisions to improve mooring safety.

The implementation of the round-circle risk assessment concept was tested through a series of simulations and real-world case studies in various mooring scenarios. The system successfully processed over 50 risk parameters, providing continuous risk updates to the crew during each stage of mooring. In one of the case studies involving a container ship in a high-traffic port, the system identified a potential collision risk due to sudden changes in wind direction and provided early warnings to the crew. As a result, the mooring operation was adjusted, preventing a possible accident.

Figure 7: Real-time assessment of the risk of mooring the vessel taking into account several factors.



Source: Authors.

The simulation results show that the proposed system reduces the probability of mooring incidents by 30% compared to traditional risk assessment methods. In addition, the time required for risk assessment was reduced by 40% due to automated data processing, allowing crew members to focus on implementing safety measures.

Modern IT solutions make it possible to create a system that can significantly improve the risk management process on board a ship. This can be done not before a mooring operation (for example) or another operation on the vessel, but already during the operation. It is practically possible to significantly increase the number of risk factors to be analyzed, moreover, with AI where we can speed up the search for information. We can also analyze the probabilities of a chain of risky events that could lead to a accident.

Further research should focus on integrating this risk assessment system with other vessel management modules, such as navigation and engine management, to create a holistic approach to vessel safety. In addition, future research can explore the use of deep learning techniques to improve the accuracy of risk prediction by analyzing large data sets.

Conclusions.

This study demonstrates that expanding the number of risk parameters and integrating AI technology significantly improves the safety and reliability of ship mooring operations. By providing real-time risk assessments and reducing human error, the round-circle risk assessment concept offers a comprehensive solution to one of the most complex aspects of maritime operations. Future research should focus on refining AI algorithms for even more accurate predictions and expanding the system's application to other critical maritime operations, such as docking and cargo handling.

The concept of circular risk assessment, improved with the proposed algorithms, can significantly improve the safety of navigation and ship operation, removing a rather large amount of tasks from the navigating officers and facilitating decision-making on the bridge.

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