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Regular Research Article

Monte Carlo-Based Risk Probability Modeling for Ship Incident

Dimas Angga Fakhri Muzhoffar*, Teddy Tumenggung, Achmad Riadi, Muhammad Arif Budiyanto, and Agung Santoso [1]

Department of Mechanical Engineering, Faculty of Engineering, Universitas Indonesia, Depok 16424

* Correspondence author: dimas.anggafm@ui.ac.id

Abstract: The shipping industry, which is a critical component of global logistics, faces persistent operational risks that threaten safety, environmental integrity, and economic stability. Traditional risk assessments, which are often reliant on descriptive statistics, fail to capture the probabilistic and multifaceted nature of maritime accidents. This study bridges this gap by developing a robust Monte Carlo simulation framework to quantify the incident probabilities of a tanker fleet. Utilizing a comprehensive dataset from a shipping company preprocesed in categorical form, including incident reports, tanker characteristics, and root causes, the model iteratively samples operational and technical variables for up to 50,000 iterations to project risk distributions and identify critical failure pathways. The results demonstrate that risk is highly contextual and not an intrinsic tanker property. The analysis reveals that mid-sized tankers are most susceptible to technical failures, such as propulsion and auxiliary machinery breakdowns, aligning with their high risk for asset loss and security breaches. Conversely, larger tankers exhibited systematically lower risk across most categories, which is attributed to advanced safety systems and stricter protocols. This study concludes that the Monte Carlo method effectively translates historical data into actionable insights, enabling proactive, precisely timed mitigations tailored to specific tanker profiles and incident types.

Keywords: Maritime Transportation, Maritime Incident, Maritime Safety, Monte Carlo Simulation, Risk Modeling, Ship Accidents.

1. Introduction

Despite being the backbone of global maritime logistics, the shipping industry continues to face significant operational risks. Data shows a rising trend in maritime accidents, with shipping accounting for the highest proportion of transport-related incidents [1], [2]. Recent events, such as the sinking of the *MV Kuala Mas* off Kupang Bay and the fire aboard the LPG tanker *B-LPG Sophia* in Bangladesh, highlight persistent safety gaps, endangering vessels, crew, cargo, the environment, and economic stability [3], [4].

Maritime accidents predominantly arise from operational failures (60% of incidents), including fires, collisions, machinery breakdowns, and design and maintenance deficiencies, such as hull fractures or flooding [5]. While human error dominates accident causation, environmental factors, such as extreme waves, further exacerbate risks by impairing vessel controllability [6].

Existing accident investigations in maritime literature often rely heavily on descriptive statistics, overlooking probabilistic dynamics and uncertainty [7], [8]. While recent studies have leveraged real-time risk prediction using

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navigation data [9], [10], [11] and global accident databases to predict the probability of an incident [12], these approaches remain limited in addressing the spatiotemporal complexity of maritime risk. For instance, Ma et al. demonstrated the value of data-driven hotspot analysis in inland waterways but did not quantify the propagation of uncertainties in multi-risk scenarios [13].

To address these gaps, particularly the need to model probabilistic dynamics, the selection of an appropriate computational technique is critical for accurate maritime risk assessment. While various methods exist, Monte Carlo simulation offers distinct advantages for this application. Unlike Markov Chains, which model systems through discrete states with fixed transition probabilities, Monte Carlo simulation is uniquely capable of modeling the complex, simultaneous interactions of multiple independent risk factors, such as gross tonnage, length, and incident type, within a single, integrated framework. This provides a more flexible and realistic assessment of incident probability for specific scenarios by directly simulating their stochastic nature [14], [15], [16]. Further, when compared to Bayesian Networks, Monte Carlo presents a more straightforward methodology for propagating uncertainty from raw input distributions to a final risk probability. This approach is particularly suited to studies that prioritize modeling inherent randomness directly, rather than establishing complex causal networks that may not be robustly supported by available data [17], [18]. Finally, in contrast to many Machines Learning (ML) models that require large datasets and significant computational resources, Monte Carlo simulation is robust even with smaller datasets, as it operates on known or estimated probability distributions. This efficiency, coupled with its superior transparency and interpretability, makes the method more accessible for policymakers, who can better understand and trust the results derived from defined distributions compared to the *black box* nature of advanced ML algorithms, which is crucial factor for informing effective risk mitigation policies [19], [20], [21].

Ultimately, this study introduces a Monte Carlo simulation framework to quantify the risk distributions from historical data. The model captures nonlinear risk cascades omitted by conventional methods by iteratively sampling the operational, environmental, and technical variables. This approach aims to enhance predictive accuracy in risk assessment, support data-driven decision-making for safety protocols, and improve operational resilience in dynamic maritime environments.

2. Materials and Methods

This study utilizes operational incident data obtained from the fleet management division of Shipping Company QRS, collected through a systematic documentary analysis of official records spanning January 2023 to July 2024: 68 incident cases. The dataset comprises a comprehensive fleet of product oil and LPG tankers' inventory information and detailed incident reports documenting tanker locations, occurrence dates, and categorized event descriptions following the 5 W +1H (Who, What, When, Where, Why, and How) investigative framework. These primary sources are supplemented by the company's internal risk assessment documents, which provide baseline parameters for establishing the probability distribution of operational hazards. The collected data encompassed all reported incidents across the Shipping Company QRS fleet during the specified period, including near-miss events and actual accidents, with each record containing sufficient technical details to serve as valid input variables for the Monte Carlo simulation modeling of maritime risk scenarios. The overall concept of this study, illustrating the sequential process from data collection to risk estimation, is summarized in Figure 1 below.

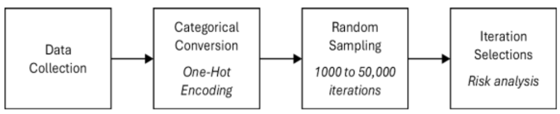


Figure 1. Basic Concept of This Study

This study starts with the collection of operational incident data, followed by the encoding of categorical variables into a numerical format suitable for simulation. The core Monte Carlo process involves iterative random sampling from the defined probability distributions to generate a multitude of risk scenarios, continuing until a predetermined number of iterations is completed to ensure result stability. The final step aggregates all scenario outcomes to compute the overall risk probability.

Figure 2 presents a comprehensive statistical description of the collected maritime incident data across the six critical operational parameters:

- Gross Tonnage (GT) Distribution: Categorized tanker capacity ranges showing incident frequency by tonnage class,
- Ships' Length: Incident occurrence relative to ship length dimensions,
- Incident Type: Systematic categorization of reported incident types (collisions, groundings, equipment failures, etc.),
- Root Cause: Causal factors breakdown using standardized marine incident classification,
- Operational Area: Spatial distribution of incidents across operational areas,
- Incident Mechanism: Detailed process mapping of how incidents occurred.

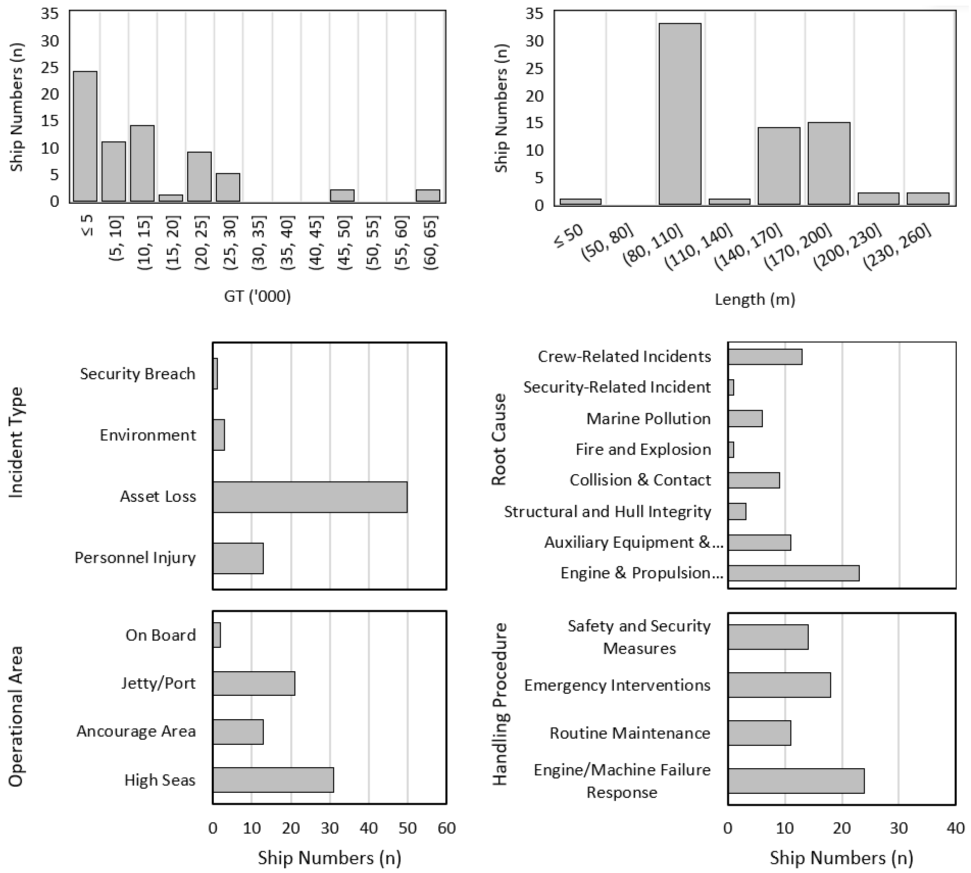


Figure 2. Collected Maritime Incident Data

To achieve the research objectives, this study employs a quantitative approach that combines descriptive and probabilistic modeling. The methodology utilizes Monte Carlo simulations to project future incident probabilities while incorporating a preliminary descriptive analysis of historical data to characterize tanker incident patterns. Key variables identified for the analysis include the following: (1) input variables consisting of incident frequency, tanker characteristics (size and age), incident categories (personnel injuries, asset losses, environmental issues, and security violations), and contributing factors (causes, locations, and incident mechanisms), and (2) output variables focusing on tanker incident risk probabilities. Because categorical data from actual incident records cannot be directly processed mathematically owing to algorithmic interpretation limitations, a data transformation process using One-Hot Encoding is implemented to convert categorical variables, including incident type, root cause, operational area, and handling procedure, into numerical formats suitable for quantitative analysis models.

This approach enables systematic risk assessment while maintaining the integrity of the original incident data characteristics. Table 1 presents a representative example of categorical data transformation using One-Hot Encoding methodology.

Table 1. An example of One-Hot Encoding Methodology

Ship Name	Incident Type				WHAT								WHERE				HOW			
	(A)	(B)	(C)	(D)	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(A)	(B)	(C)	(D)	(A)	(B)	(C)	(D)
MT 1	0	1	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	1	0
MT 2	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	1
MT 3	0	0	1	0	0	0	0	0	0	1	0	0	0	0	1	0	0	1	0	0
MT 4	0	1	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	1	0	0
MT 5	0	0	0	1	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	1

* **Incident Type**: (A) Personnel Injury, (B) Asset Loss, (C) Environment, (D) Security Breach; **WHAT**: (A) Engine and Propulsion Machinery, (B) Auxiliary Equipment and Machinery, (C) Structural and Hull Integrity, (D) Collision and Contact, (E) Fire and Explosion, (F) Marine Pollution, (G) Security-Related Incident, (H) Crew-Related Incidents; **WHERE**: (A) High Seas, (B) Ancourage Area, (C) Jetty/Port, (D) On Board; **HOW**: (A) Engine/Machine Failure Response, (B) Routine Maintenance, (C) Emergency Interventions, (D) Safety and Security Measures.

Building on these results, the Monte Carlo simulation implements stratified random sampling across all input variables through iterative realizations ranging from 1000 to 50,000 iterations. The sampling adheres to the empirically observed right-skewed distribution of fleet characteristics for numerical parameters, such as gross tonnage, length, and age. After this initialization, the methodology addresses the skewness of the data through a mixed discrete-continuous distribution [12], partitioning the GT spectrum into three intervals: 1479–35,000 GT at 80.7% probability, 45,000–50,000 GT at 12.1%, and 60,000–63,005 GT at 7.2% to ensure proportional representation [22], [23], [24], [25], as represented mathematically in Equation 1:

$$X = \begin{cases} Uniform(1479,\ 35{,}000), & if\ r \leq 33{,}521 \\ Uniform(45{,}000,\ 50{,}000), & if\ 33{,}522 \leq r \leq 38{,}521 \\ Uniform(60{,}000,\ 63{,}500), & if\ r > 38{,}521 \end{cases} \quad (1)$$

where X is the cumulative probability for a ship (GT, length, and age) and r is the stratification control variable in the case of 50,000 iterations: $r{\sim}Uniform(0,\ 50{,}000)$. Advancing to categorical variables, the transformed one-hot encoded data underwent weighted random sampling based on historical incidence frequencies, thereby preserving the probabilistic integrity of the operational scenarios. This sequenced approach systematically propagates uncertainty through the model while maintaining computational efficiency, as shown in **Equation 2**:

$$x = \begin{cases} 1 & if\ U \leq p \\ 0 & if\ U > p \end{cases} \quad (2)$$

where x is the cumulative probability for categorical variables (Incident Type and Root Cause) and p is the category probability in $U{\sim}Uniform(0,\ 1)$.

3. Results and Discussions

Monte Carlo simulations were performed across multiple iteration scales (1000, 5000, 10,000, 20,000, 30,000, 40,000, and 50,000 iterations) to ensure statistical convergence and robustness. For numerical tanker characteristics, including GT, length, and age, the simulation implemented bounded uniform sampling constrained by empirically derived minimum and maximum values from the fleet dataset, with each parameter sampled independently per iteration. Categorical variables, previously transformed into numerical representations through one-hot encoding, were simulated using weighted random sampling based on historical occurrence frequencies to maintain the empirical probability distributions. The resulting outputs were systematically collected, normalized, and visualized using histograms.

These graphical representations demonstrate (1) the distribution of key operational parameters and (2) the convergence behavior across successive iteration levels. Figure 3 presents the histogram for each incident type, where the x-axis represents the GT distribution (see Figure 2) and the y-axis represents the frequency. These histograms illustrate the distribution characteristics of each incident type at the various iteration levels.

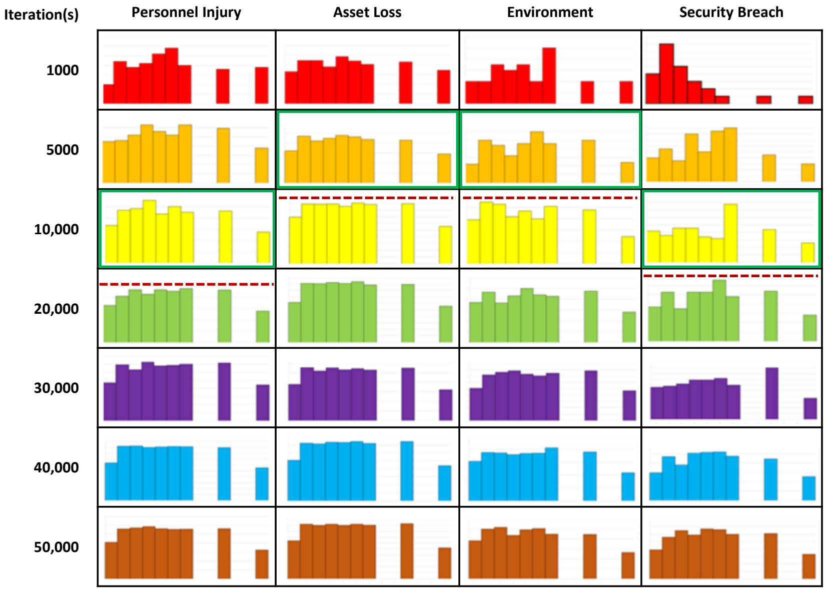


Figure 3. Monte Carlo Simulation on Incident Type

The saturation of the frequency distribution for each incident type is indicated by a red dashed horizontal line. This line was determined by analyzing the reduction in deviation between successive iteration bins, where the binning ranges were defined according to the GT categories established in Figure 2. The saturation point signifies the iteration count beyond which additional sampling yields insignificant changes in the results, marking a point of diminishing returns. This enables a quantitative verification of the simulation's stability and demonstrates the progressive refinement of the probabilistic outcomes. The analysis confirms that a stable distribution is achieved at 10,000 iterations for Personnel Injury and Security Breach incidents and at 5000 iterations for Asset Loss and Environmental Impact incidents. While the specific convergence rate is beyond the primary scope of this study on Monte Carlo applications, the established saturation points robustly indicate result stability.

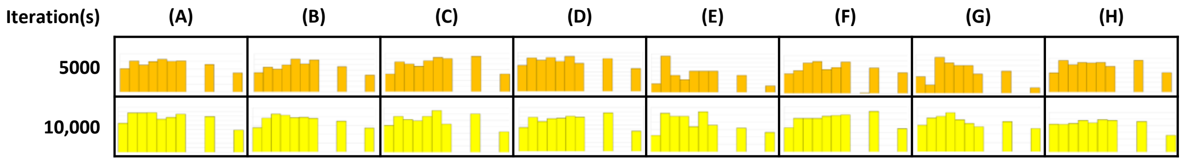
Therefore, all subsequent risk analyses were based on these stabilized results. Table 2 summarizes the tankers exhibiting the highest and lowest risk levels identified from the selected iterations.

Table 2. Tankers with Highest and Lowest Risks

Incident Type	Iteration(s)	Tanker with High Risk (GT ‘000)	Tanker with Low Risk (GT ‘000)
Personnel Injury	10,000	15–20	> 60
Asset Loss	5000	20–25	> 60
Environment	5000	25–30	≤ 5
Security Breach	10,000	30–35	> 60

The data shows that high-risk tankers vary significantly by incident type, even within a fixed iteration count. Furthermore, larger tankers consistently demonstrated a lower risk level than other tanker size classes. The simulation results revealed that high-risk tankers vary significantly by incident type, even at a fixed iteration count. This indicates that risk is not an intrinsic property of a tanker but is highly contextual and contingent upon a specific operational hazard. For instance, tankers in the 15,000–20,000 GT range were the most susceptible to personnel injury, whereas the 30,000–35,000 GT class was identified as the highest-risk cohort for security breach incidents.

A consistent trend also emerges regarding tanker size: larger tankers (> 60,000 GT) demonstrate a systematically lower risk level across multiple incident categories than other size classes. The exception to the environmental impact risk was the smallest tanker (≤ 5000 GT), which presented the lowest risk. This finding reinforces the principle that risk is multifaceted and governed by distinct physical and operational mechanisms for different types of incidents. Accordingly, Figure 4 presents a root cause histogram derived from the Monte Carlo simulation outputs at selected iteration counts.



* (A) Engine and Propulsion Machinery, (B) Auxiliary Equipment and Machinery, (C) Structural and Hull Integrity, (D) Collision and Contact, (E) Fire and Explosion, (F) Marine Pollution, (G) Security-Related Incident, (H) Crew-Related Incidents.

Figure 4. Monte Carlo Simulation on Root Cause

The simulation results provide a detailed probabilistic mapping of root causes across different tanker size categories at selected iteration counts (5000 and 10,000 iterations). This analysis revealed that the prevalence of specific failure mechanisms is intrinsically linked to the GT class of the tanker. This finding can be directly correlated with the prior risk-level results presented in Table **2**, effectively explaining why certain incident types are more probable for certain tanker-size classes. The detailed probability distributions for these root causes, as drawn from the simulation outputs (see Tables 3 and 4).

The results indicate that mid-sized tankers (20,000–25,000, 25,000–30,000, and 30,000–35,000 GT) consistently show the highest probability for root causes linked to Engine and Propulsion Machinery (A), and Auxiliary Equipment and Machinery (B), with values often exceeding 4.0% and 2.0%, respectively. This aligns perfectly with the identification in Table 2, where this size range is high-risk for asset loss and security reaches, incidents often precipitated by these operational and technical failures [26] and are consistently highlighted in industry casualty reports [5].

Table 3. Probability of Root Cause at 5000 Iterations

GT ('000)	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)
≤5	3.04%	1.42%	0.32%	1.34%	0.08%	0.72%	0.12%	1.58%
(5, 10]	4.04%	1.82%	0.54%	1.72%	0.34%	0.84%	0.06%	2.60%
(10, 15]	3.54%	1.68%	0.50%	1.60%	0.16%	1.12%	0.26%	2.24%
(15, 20]	3.98%	1.98%	0.46%	1.74%	0.12%	1.18%	0.22%	2.44%
(20, 25]	4.28%	2.42%	0.56%	1.54%	0.20%	0.88%	0.20%	2.40%
(25, 30]	4.00%	2.06%	0.62%	1.80%	0.20%	0.96%	0.20%	2.44%
(30, 35]	4.06%	2.36%	0.60%	1.44%	0.20%	1.16%	0.14%	2.12%
(35, 40]	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
(40, 45]	0.00%	0.00%	0.00%	0.00%	0.00%	0.02%	0.00%	0.00%
(45, 50]	3.60%	1.86%	0.64%	1.68%	0.16%	0.94%	0.16%	2.62%
(50, 55]	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
(55, 60]	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
(60, 65]	2.48%	1.24%	0.32%	1.18%	0.06%	0.76%	0.04%	1.60%

* (A) Engine and Propulsion Machinery, (B) Auxiliary Equipment and Machinery, (C) Structural and Hull Integrity, (D) Collision and Contact, (E) Fire and Explosion, (F) Marine Pollution, (G) Security-Related Incident, (H) Crew-Related Incidents.

Table 4. Probability of Root Cause at 10,000 Iterations

GT ('000)	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)
≤5	3.19%	1.37%	0.42%	1.08%	0.11%	0.74%	0.15%	2.11%
(5, 10]	4.35%	1.92%	0.56%	1.55%	0.26%	1.03%	0.19%	2.10%
(10, 15]	4.34%	2.15%	0.51%	1.36%	0.24%	1.03%	0.20%	2.17%
(15, 20]	4.36%	2.08%	0.49%	1.49%	0.24%	1.03%	0.22%	2.39%
(20, 25]	3.65%	1.95%	0.56%	1.51%	0.17%	1.10%	0.18%	2.21%
(25, 30]	3.86%	1.97%	0.65%	1.60%	0.27%	1.12%	0.16%	2.45%
(30, 35]	4.20%	1.91%	0.44%	1.56%	0.18%	1.14%	0.14%	2.40%
(35, 40]	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
(40, 45]	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
(45, 50]	3.94%	1.74%	0.60%	1.75%	0.16%	1.25%	0.17%	2.31%
(50, 55]	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
(55, 60]	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
(60, 65]	2.45%	1.35%	0.32%	0.92%	0.13%	0.71%	0.13%	1.26%

* (A) Engine and Propulsion Machinery, (B) Auxiliary Equipment and Machinery, (C) Structural and Hull Integrity, (D) Collision and Contact, (E) Fire and Explosion, (F) Marine Pollution, (G) Security-Related Incident, (H) Crew-Related Incidents.

Conversely, the largest tankers (> 60,000 GT) demonstrate a systematically lower probability across nearly all root-cause categories. For example, the likelihood of Engine and Propulsion Machinery (A) is nearly half that of medium-sized tankers. This also quantitatively supports Table 2, which indicates that these tankers present the lowest risk. This is attributed to factors associated with larger tankers, such as more robust safety management systems, advanced technology, stricter regulatory compliance, superior

The exception of Environmental Impact risk, for which Table 2 identified the smallest tankers (≤ 5000 GT) as the lowest risk, was also clarified by root cause analysis. While these tankers may have a higher relative frequency of operational errors (Engine and Propulsion Machinery (A): ~3.2%), their consequences are limited by their smaller cargo capacity, resulting in a lower overall environmental risk score, as they would release a smaller volume of spill in a casualty scenario [27], [28], [29]. This aligns with the findings of ITOPF [31], whose data confirms that while smaller tankers are involved in more grounding and collision incidents, the total spill volume is dominated by casualties involving

maintenance protocols, and more experienced crew, all of which mitigate fundamental risks [27], [28], [29] as required and enhanced under stringent ISM Code compliance [30].

larger vessel types. Therefore, these histograms move beyond identifying what incidents happen to which tankers begin to illuminate the underlying mechanisms that drive these risks, providing invaluable insight for targeted safety interventions.

By leveraging this specific data, a mitigation recommendation process was conducted for the actual operation based on the Monte Carlo simulation results [12]. These mitigation strategies were structured according to incident categories and aligned with the Shipping Company QRS's existing Risk Assessment framework, as exemplified in Table 5.

Table 5. An example of Risk Assessment Framework

Hazard Category	Risk	Losses	How to Eliminate Losses
Mechanical	Engine Failure (Main Engine, Auxiliary Engine)	Loss of propulsion, Loss of power generation, Operational delays	Regular Maintenance, Use monitoring tools, QA/QC for components, Crew training, Spare parts inventory, Manufacturer (after sale) contracts, Regular audits and reviews
	Pump Failure	Loss of stability, Loss of cargo, Operational delays	

To illustrate, for a tanker of 22,156 GT and 180 m in length that experienced a machinery and auxiliary equipment incident, the prescribed control measures from the Shipping Company QRS's Risk Assessment include implementing routine maintenance and inspections, enforcing quality control for all components, utilizing onboard monitoring and diagnostic systems, and conducting regular audits and reviews. These actions were prescribed to reduce the potential risk level from its current state.

4. Concluding Remarks

Based on the conducted testing and analysis, the developed simulation model demonstrated a robust capability for projecting future incident probabilities for specific tankers. Through up to 50,000 Monte Carlo iterations, the model successfully maps incidents by key parameters such as tanker specifications, incident type, and root causes. It provides quantitative probabilities of incidents alongside their likely root causes, enabling the design of proactive, preemptive risk management strategies.

A key limitation of this study is its use of a dataset from a single company, which constrains the generalizability of the results. To further advance this research, subsequent studies should utilize longer temporal datasets and integrate proprietary with public maritime data to improve historical validity and generalizability. Expanding the volume and diversity of input data will yield more accurate and reliable projections. Future work should also incorporate deeper analysis of operational contexts, such as specific routes and handling procedures, and include additional environmental and technical parameters to refine temporal estimates and support more precise timed interventions.

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