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RESEARCH ARTICLE

Probabilistic Risk model of Ship Allision Accidents with Offshore Platforms

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Abstract

This paper proposes a Bayesian Network-based framework for risk assessment and probability estimation of vessel-platform allision accidents, using a novel technique that derives probabilities from incidental data. A dataset of 557 allision incidents collected from multiple open source agencies is analysed to identify causation patterns. Basic causes could only be determined for 375 incidents, with supply vessels involved in 61% of cases. Statistical analysis revealed that vessel type and the month of occurrences are significantly associated, and most incidents arose during cargo transfer operations. Fixed installation accounted for the majority of allisions with moving vessels, and human error emerged as the leading contributor (30%). Building on these insights, a Bayesian Network model is developed incorporating 42 identified causes, three causal factors and four consequence levels. Using a recent probabilistic approach, probabilities of basic causes are derived from annual allision occurrence rates. The BN model is then applied to predict annual allision probabilities and to conduct sensitivity analyses. Results show that weather-related causes and misalignment errors exert the strongest influences on accident probabilities. The methodology is transparent and holistic in providing better discernment of the causation probability of allision accidents.

Keywords Vessel–platform allision accidents; Bayesian networks; Causal factors; Basic causes; Sensitivity analysis

1 Introduction

Accident scenarios such as fires and explosions, hazardous material releases, vessel collisions, ship allisions and crane accidents are persistent safety concerns in offshore and maritime industries. These events have repeatedly caused fatalities, structural damage to the facility and environmental consequences (EMSA, 2023; HSE, 2023; Havtil, 2023; USCG, 2023). Disasters like the Piper Alpha, the BP Deepwater Horizon and the Cidade de São Mateus FPSO have compelled the offshore industry to adopt structured approaches to risk assessment and management (UK Oil and Gas, 2010; Norazahar et al., 2014; Bhardwaj et al., 2021). A thorough understanding of both the causes and occurrence probabilities of accidents is fundamental to enhancing the safety performance of offshore installations (Bhardwaj et al., 2017, 2022b). While probabilistic methods are well established for high-frequency, high-impact events like fires and explosions (Bhardwaj et al., 2021; Khakzad and Reniers, 2018; Spouge, 2017; Wang et al., 2018), allision remain underexplored despite being low frequency but high consequence events. Between 2013 and 2020, allision incidents accounted for 15% of all recorded accidents in China's coastal waters, making it the second most frequent accident category (Liu et al., 2021).

An allision occurs when a moving vessel strikes a fixed or floating structure such as an offshore platform, FPSO, bridge pier or wind turbine. This differs from a collision, which involves two moving vessels (UK Oil and Gas, 2010; Zhao et al., 1994. Due to their high frequency and severe consequences, ship collisions are among the most thoroughly investigated types of maritime accidents. (Graziano et al., 2016; Silveira et al., 2013), subsequently quantified through a range of frequency estimation models integrating statistical datasets and experts' elicitation (Čorić et al., 2021) and, thus, not subject to analysis in the present study. This paper focuses on allision accidents, which are rare yet significant for seagoing vessels and stationary platforms. The allision is sometimes known as "contact (with fixed and floating structure)" and "collision" in ship accident databases such as European Maritime Safety Agency (EMSA, 2023), Marine Accident Investigation Branch, (MAIB, 2023) and United States Coast Guard, (USCG, 2023); however, "allision" is the terminology uses is primarily based on the authors preference. Regulators such as

Article Highlights

- Bayesian network framework for allision risk.
- Data-driven causation analysis.
- Estimation of the probability of failure based on real data.

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the Norwegian Ocean Industry Authority (Havtil, 2023) and the Health and Safety Executive (HSE, 2023) UK classifies allision as a major accident hazard requiring targeted risk assessment.

Subsequently, researchers and industrials have put effort into understanding and modelling allision scenarios to prevent and mitigate them. UK Oil and Gas Industry Association (UK Oil and Gas, 2010) provides guidelines for contingency plans and measures to avoid allision incidents. More emphasis is placed on the use of collision detection systems.

Formal risk assessment of allision has been attempted for more than three decades (Xiao et al., 2022). Earlier, Zhao et al. (1994) developed a human error focused probabilistic framework, where causation probabilities are calculated through fuzzy methods. Other probabilistic allision models, such as Ship Offshore Platform Collision Risk Assessment (SOCRA), have been designed to integrate scenarios involving both ramming and drifting collisions (van der Tak and Glansdorp, 1995). COLLIDE model considers navigation errors arising from equipment faults, weather effects and human factors (Haugen, 1994). More commercial software, such as CRASH by DNV, COLRISK by Anatec, and MANS from MSCN (Netherlands), exists that utilises shipping traffic databases for probabilistic modelling of allision (Geijerstam and Svensson, 2008; UK Oil and Gas, 2010). These software are susceptible to model assumptions, which require significant upgrading with the advancement of technology (Geijerstam and Svensson, 2008; Hassel et al., 2021; Mujeeb-Ahmed et al., 2018). In general, such models provided a baseline but were limited in scope and increasingly outdated.

Recent contributions have applied modern probabilistic tools, simulations and data-driven approaches. Bayazit and Kaptan (2024) analysed 112 allisions using the well-known human factor taxonomy for classification. Later, Kaptan and Bayazit (2024) adopted a data-driven BN approach and identified ship type, wind, and ship age as the most influential factors in predicting the severity of accidents in port areas. While these studies are comprehensive, their findings primarily focus on the probability of allision during port manoeuvres. Ceylan et al. (2021) also used a human factors-oriented approach, applying the System Theoretic Accident Model and Process to ship allision accidents. Using a real-time case study of an allision in narrow waters, they emphasised that such accidents are system-based, dynamic and complex. Hörteborn et al. (2025) developed a Monte Carlo-based ship bridge simulator showing its value for early design phases. Son and Carlo studied ship allision with offshore wind turbines, suggesting a minimum safe route width of 8 943 m, considering future traffic demands.

Different perspectives and techniques in the literature have analysed allision scenarios. For example, the Automatic Identification System (AIS) that provides ship trajectory data, and has been employed extensively for the probabilistic allision assessment (Hassel et al., 2021; Mujeeb-Ahmed et al., 2018). Hörteborn and Ringsberg (2021) analysed bridge allision probability using ship maneuvering information and AIS data to identify accident scenarios. However, these models, being simulation-based, generally target a specific extreme event and therefore leave multiple key risk factors insufficiently considered or unaddressed. That said, there are alternative models that probabilistically evaluate particular scenarios or isolated risk elements. For example, Chen and Moan (2004) focused on FPSO and tanker allision events during offloading operations, analyzed through drive-off frequency assessment.

Another common approach to modeling allision scenarios involves using the likelihood of a vessel being on a collision course combined with the causation probability (probability that the vessel stays on a collision course) (Chen and Moan, 2004; Haugen, 1991; Haugen and Moan, 1992). These probabilistic accident models emphasise the spatial distribution of maritime traffic and the locations of offshore installations (Xiao et al., 2022).

Geometric representations and dynamic characteristics due to the use of current traffic data are the advantages that make these models very practical. However, their main limitation lies in the simplistic estimation of causation factors and probabilities, as observed in studies such as Hörteborn and Ringsberg (2021) and Pedersen (2002) .

These studies highlight the important shift from deterministic to probabilistic and data-driven approaches; however, several limitations remain to be addressed. For instance, most probabilistic models often treat human error, environmental conditions and ship/traffic characteristics in isolation. Integrated frameworks that can capture interdependencies remain scarce (Xiao et al., 2022). It is clear that Software-based, geometric and AIS-based models emphasise the final allision probability rather than inherent causal factors.

Xiao et al. (2022) have presented a comprehensive review, revealing that almost all allision risk models overlook key risk factors necessary for a holistic representation of such scenarios. They further emphasized the need for an in-depth analysis of causal factors, particularly human elements and weather influences to more accurately predict incident probabilities. Challenges such as larger vessels, denser offshore wind farms and climate weather variability are rarely explicitly addressed, leaving gaps in inadequate assessment (Son and Cho, 2024). Eliminating the probability of allision is challenging, as procedural violations often become normalized within routine operations and are difficult to incorporate effectively into an organization's safety management system (Oltedal, 2012). Industrialists require tangible information, including the probability of accidents and their basic causes, to allocate investments in safety management.

Since allision accidents are less frequent than collisions, and incident databases are incomplete or inconsistent. This results in uncertain prior probabilistic models and general adaptability across regions (Zhen et al., 2023).

Recent developments have introduced more flexible tools like Bayesian networks (BNs) for portraying causal frameworks and characterising probabilistic dependencies among the variables. Bayesian networks are more flexible and sophisticated than traditional causal analysis techniques. Therefore, BNs have been used in many sectors as a tool for risk modelling and analysis with uncertainty (Amin et al., 2018; Cai et al., 2012; Khakzad et al., 2011, 2013). BNs have a profound application among the approaches used for maritime accident analysis as they can easily represent dependencies among the events (Zhang et al., 2013; Zhang et al., 2016). Fan et al. (2020) collected maritime accident data from the Marine Accident Investigation Branch (MAIB) and the Transportation Safety Board of Canada (TSB) between 2012 and 2017, and developed a data-driven BN that emphasised the importance of the human factor in addition to other risk-influencing factors on accident type. In a similar approach, Liu et al. (2021) have trained BN with machine learning algorithms to develop a maritime accident model. They have gathered accident data on China's coastal area to analyse the impact of risk-influencing factors on accident severity.

These BN models have generally addressed maritime accidents in aggregate rather than focusing on specific types. a major challenge with BN is the high uncertainty in prior and conditional probabilities. To address this, expert elicitation is often combined with historical data (Zhang et al., 2013; Zhang et al., 2016). However, reliance on expert opinion introduces subjectivity. This limitation can be reduced by carefully integrating reliable historical data (Hassel et al., 2021).

To bridge the above-stated gaps, this study integrates several causal factors in a single BN model. The main intricacy of the use of BN is estimating prior probabilities of the parent nodes (Li et al., 2014). Therefore, this study adopts a novel probabilistic technique for prior distribution, reducing subjectivity (Bhardwaj et al., 2024). The methodology proposes a balance of the use of historical data in probabilistic modelling to strengthen both reliability and interpretability.

2 Methodology

This section presents the proposed probabilistic framework for ship allision accidents with offshore installations. Figure 1 shows the methodology outline with the main steps explained as follows. The probability of accident occurrence can be estimated using probability methods and historical data (HSE Books, 2017; Yin et al., 2021). The offshore industry is responsible for recording major accidents, minor incidents, and precursor events to the national authorities so that they can adopt safety measures (BSEE (Bureau of Safety and Environmental Enforcement), 2023; eMARS, 2023). However, offshore accident data suffer from scarcity and underreporting of incidents; thus, any adopted methodology should address these issues (Zhen et al., 2023). Offshore scenarios involve different risk factors to the initiating events than onshore scenarios; thus, the accidents have distinct characteristics (Almeida and Vinnem, 2020; Bhardwaj et al., 2018, 2022a; Song et al., 2016).

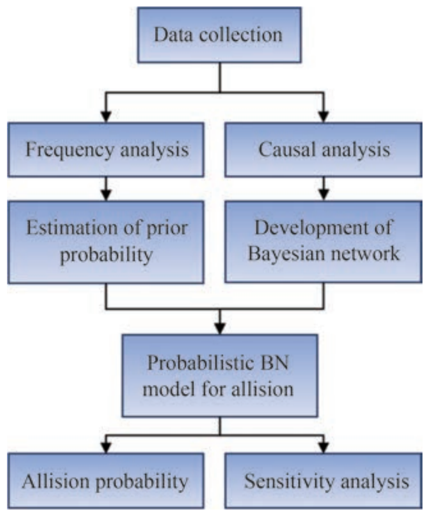

Figure 1 Proposed methodology

The first step consists of collecting allision incidental data from offshore databases and investigation reports from the literature. Secondly, the data is interpreted in two ways: the data is thoroughly analysed to reveal significant insights about the circumstances. This leads to the development of a causal framework among the main event (allision), intermediate events and last identified causes (basic causes).

This information is further utilised to develop a causal network using a BN model. The different nodes can be positioned with identified basic causes, intermediate causes and main allision events. Connections are established to represent causal relationships as per the data analysis.

From the analysis of the data, the frequency of each basic cause can be calculated from the number of occurrences in the database. A recent approach (Bhardwaj et al., 2024) This paper utilises prior frequencies in the posterior probability of basic causes. Once the BN is characterised with prior probabilities and conditional probabilities, it can be used to perform probabilistic analyses such as allision probability prediction and sensitivity analysis of basic causes. A brief introduction to the probability estimation approach and Bayesian theory is provided in the following subsections.

2.1 Estimation of the prior probability

In the previous study (Bhardwaj et al., 2024), an approach for prior probabilities of allision is proposed, which has two major steps: 1) ranking of allision basic causes from incident data collection 2) posterior probability estimation of basic causes of allision accidents.

As per the relative frequency, each basic cause is ranked from least to highest observed. This approach has the added advantage of identifying and placing more causes as per the expert's experience. A method known as the Deck of Card Method (DCM) (Corrente et al., 2021a; Figueira and Roy, 2002) is employed to assign normalized weights to these fundamental causes. This method introduces a novel framework that converts accident occurrences into occurrence rates of the basic causes, utilizing normalized weights derived from the DCM. The annual frequency of accidents is converted into occurrence rates of each basic cause. Finally, Hierarchical Bayesian Analysis (Kelly and Smith, 2009) is carried out to estimate the probability of the basic causes based on the posterior mean of their annual occurrence rates.

Due to space limitations, this approach is not discussed in details here; further information can be gathered from (Bhardwaj et al., 2024). For completeness, a generic application of the method is provided in Appendix A.

2.2 Bayesian network

Formal risk assessment involves probabilistic techniques that develop causal relationships among leading events and their precursors. Fault tree analysis, event tree analysis, bow-tie method, and reliability block diagrams are examples of commonly used methods in the offshore sector. Moreover, international standards (IEC 31010, 2019) emphasise hazard identification as the primary step in accident scenario modelling. This study adopts a Bayesian Network (BN) model to describe allision accidents in the offshore sector. The Bayesian Network (BN) is a probabilistic framework for making inferences under uncertain information and is capable of analysing complex interrelations and dependencies among model parameters. Compared to traditional methods, BN is acknowledged for its capability of assimilating empirical data with expert elicitation and presenting causal relationships while showing graphical means.

A Bayesian Network (BN) is a directed acyclic graph (DAG) consisting of nodes and arcs that form a probabilistic framework. The nodes represent basic random variables, while the arcs illustrate the dependencies among them by linking child nodes to their parent nodes. These connections in a BN define the probabilistic relationships between basic and dependent variables.

The basic structure of a BN network provides a qualitative description of the problem. The Conditional Probability Tables (CPTs) of discrete variables define the quantitative relationships among the variables. A CPT offers a comprehensive representation of the probabilistic interactions, capturing all potential dependencies between parent and child nodes. The Bayesian Network is fundamentally based on Bayes' theorem, expressed as

$$p\left(\theta \middle| y\right) \propto p\left(y|\theta\right) p\left(\theta\right) \tag{1}$$

Here, y denotes the observed data, and θ represents the model parameter capable of generating that data. $p\left(\,|\,\right)$ denotes the probability density function under given conditions. Specifically, $p\left(\theta\right)$ is the prior probability, $p\left(y|\theta\right)$ is the likelihood function, and $p\left(\theta\middle|y\right)$ is the posterior distribution. A BN expresses the joint probability distribution over a set of discrete random variables Y where Y can be represented as

$$Y = \left(Y_1, Y_2, Y_3, \cdots, Y_n\right) \tag{2}$$

where n is the total number of discrete random variables. The joint probability distribution of Y (as shown in Eq. 2) can be obtained by multiplying all prior probabilities and their corresponding conditional probability distributions.

$$P\left(y_1, y_2, y_3, \cdots, y_n\right) = \prod_{i=1}^{n} P\left(y_i/\mathrm{pa}\left(y_i\right)\right) \tag{3}$$

where the term $P\left(y_i/\mathrm{pa}\left(y_i\right)\right)$ is the conditional probability of y_i given its parent variables $\left(\mathrm{pa}\left(y_i\right)\right)$.

The first use of BN is qualitative, describing the logical structure of the events. Then, a quantitative analysis is conducted to estimate the probability of the top event occurring, which requires predicting the probability of the occurrence of the basic causes. To achieve this objective, relevant data is collected as described in the following subsections.

3 Results

This section presents the results of applying the proposed methodology to estimate the allision accident probability.

3.1 Analysis of the incidental data

Information on offshore accidents and incidents can be obtained from research studies, official and industrial reports, news articles, and accident databases (Christou and Konstantinidou, 2012). The collected information may provide significant insights into the causal evolution of an accident. Aiming to collect and analyse some data as described below.

3.1.1 Data collection

The information from (Norwegian Ocean Industry Authority (Havtil), 2023) and (BSEE (Bureau of Safety and Environmental Enforcement), 2023) databases is collected to comprehend the trend of reporting for allision incidents in the offshore sector. Moreover, broad ship accident data from (EMSA (European Maritime Safety Agency), 2023; MAIB (Marine Accident Investigation Branch), 2023; USCG (United States Coast Guard), 2023) has also been studied. These publicly available reports reveal primary accident indicators, such as the number of occurrences, ships lost, and casualties, with respect to time and ship type. However, these reports often overlook in-depth causal factors (immediate causes) and basic causes of the accidents, which are often not described. In addition, extensive information from the literature review of scientific papers (discussed in the Introduction section) is collected to understand and characterise allision accidents.

This paper utilises two comprehensive allision incident data sets from UK Continental Shelf (UKCS) (Robson, 2003; Loughney et al., 2019) as primary information for frequency analysis. The HSE is a pioneer organisation and authority based in the UK responsible for health and safety-related issues onshore and offshore.

These data sets are consulted since they provide more layers of investigation that can lead to better and more credible accident scenarios. This section aims to provide complete statistics on allision incidents involving offshore oil and gas platforms on the UKCS between 1975 and 2016. It should be noted that the available data are limited and cover only a small share of global accidents.

3.1.2 Vessel types involved in allisions

The data sets are scrutinized for the vessel type involved in the allision incidents. Figure 2 shows that supply vessels account for 61% of involvement in allision incidents, followed by standby vessels (15%) and other vessels (15%). Earlier studies also identified that allision risk is more apparent on general supply (cargo) vessels (Liu et al., 2021). The types of other vessels are further displayed by their distribution as driver support (6%), Anchor handler (3%), Merchant tanker (2%) and Tug (2%). The remaining vessel types have a distribution of around 1% each.

This section further uses the chi-square test to check the dependence between the month of the year and vessel type. The chi-square test distinguishes the observed and expected frequencies by statistical difference. The independence test using chi-square is applied to the statistical dependence between these two variables. First, two hypotheses (H_{null} and H) are adopted as H_{null} There is no significant relationship between the month of year and the type of vessel. H There is a significant relationship between the month of year and the type of vessel.

The chi-square statistic (χ^2) was calculated as 75.21 based on the observed and expected frequencies. The critical value of χ^2 at a 95% significance level was determined to be 60.48. Since the calculated χ^2 exceeds the critical value, the null hypothesis (H_{null}) is rejected. This indicates that the occurrence of allisions involving different vessel types is statistically dependent on the month of the year.

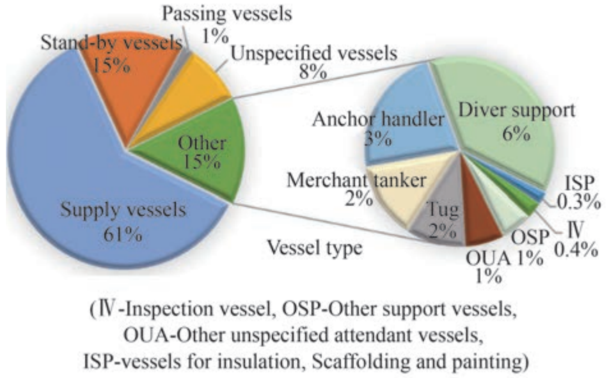

Figure 2 Distribution of vessel types involved in allision

Table 1 Number of allision incidents against months of year and type of vessels

Months of year	Type of vessels				
	Supply vessels	Stand-by vessels	Other attendant	Passing vessels	Unspecified vessels
January	50	11	7	1	8
February	47	4	6	1	3
March	41	7	5	1	4
April	32	7	10	0	0
May	35	11	14	1	0
June	24	3	4	2	4
July	30	15	17	2	4
August	29	10	8	2	0
September	31	15	12	0	0
October	43	12	9	0	3
November	37	8	9	0	0
December	44	4	6	0	3

3.1.3 Vessel's operating circumstances

The basic operating circumstances during the allision incidents are shown in Figure 3. It is evident from the figure that most of the incidents occur during cargo transfer (23%), approaching installation (18.5%) and cargo unloading (11%). Other important operations, according to their distribution in allision events are Close Support (5%), Diving Operations (4%), Anchor Handling (3%), Cargo Unloading–Containers (2%) and Cargo Loading (2%).

3.1.4 Installation types involved in allision

Furthermore, the database is scrutinised for offshore installations involved in incidents related to allisions with vessels. The results of this analysis are presented in Figure 4 for the involved installation. Notably, fixed installations (fixed steel, fixed concrete, jacket, and tension leg) account for a significant share of incidents, followed by floating installations. Further, the breakdown of the floating installations is provided in the figure. Semi-submersible drilling units are involved in 27% of the incidents followed by Semi-submersible crane support 4% and Floating production units 4%.

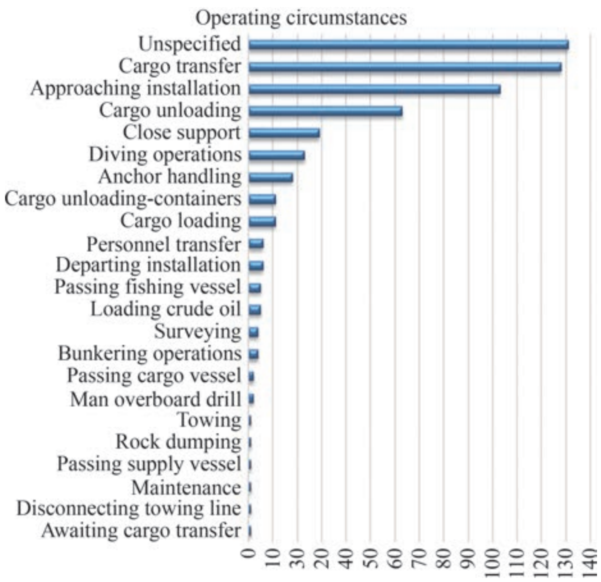

Figure 3 Distribution of vessel's operating circumstances

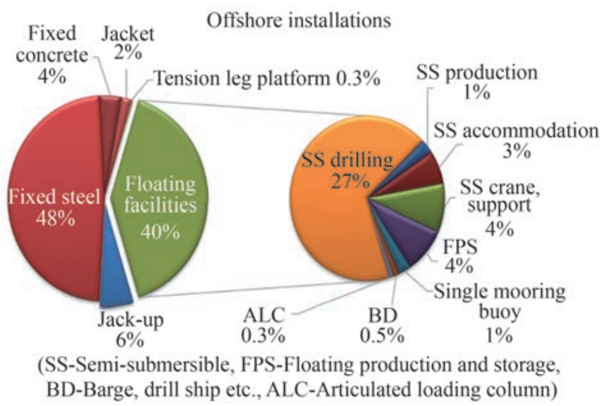

Figure 4 Distribution of allision incident with type of offshore installations

3.1.5 Distribution of incidents by severity

Different databases classify the severity of incidents in different ways. This study organizes incidents into groups for analysis, mainly using the HSE taxonomy described in the reports (Robson, 2003; Loughney et al., 2019). The impact of allision on offshore installation (damage) is acknowledged as severe, moderate, minor and none.

Though 3% of incidents are heightened to serrious accidents and 10% are moderate, yet the major concern is that 53% of them are minor incidents. 15% of causes remained unknown and thus unspecified in the database (Figure 5).

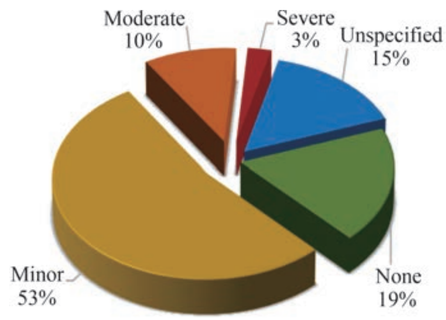

Figure 5 Distribution of offshore installation damage class

3.1.6 Causal factors of allisions

The analysis of results in terms of causal factors of allision incidents is shown in Figure 6, which displays their distribution in the dataset. Human errors contribute to most accidents (30%), while equipment failures account for 22% and external factors for 15%. This study aims to identify the causes of these incidents; however, the limited information in the data means that 33% of the immediate causes remain unknown. This is a common issue with the analysis of incidental data, as a significant portion of incidents remains unanalyzed due to a lack of reporting, inadequate understanding of the incident, or insufficient resources.

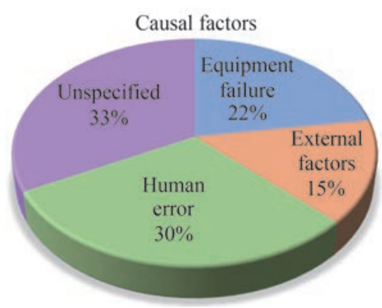

Figure 6 Causal factor of allisions

3.1.7 Basic causes of allisions

Risk assessment can be effectively carried out if a good understanding of the basic causes leading to an accident is achieved. The thorough analysis of compiled data produces a generic causation structure, exposing the next layer of hazard identification. It is improvised to break down further possible weather elements that are vital for allision scenarios. As discussed in section 3.1.1, other databases were consulted, which identified that heavy rain, thick fog, extreme waves and wind conditions are the main weather conditions causing allision. The quantitative details are derived from expert elicitation from the author's previous study (Bhardwaj et al., 2024).

Of the 557 allision incidents analyzed, basic causes were identified for 375 (Figure 6). These have been slightly revised according to the authors' interpretation. However, the basic causes reflect only the final recorded factors and may not represent the underlying root causes that contributed to the events.

First, in Figure 7, the distribution of basic causes for equipment failure are depicted. Engine failures are mostly due to control equipment failures, constituting 21%, while engine power failures include 10% of overall equipment failures. Failures of Dynamic Positioning (DP) equipment include control failures (6%), computer failures (1.6%), electrical failures (1.6%), and remote-control failures (0.8%). Other critical equipment requiring particular attention due to their susceptibility to failure includes thrusters, steering systems, mooring equipment, and electrical or power-related components. Other causes, such as propeller, crane, and rudder failures, each account for approximately 0.8%.

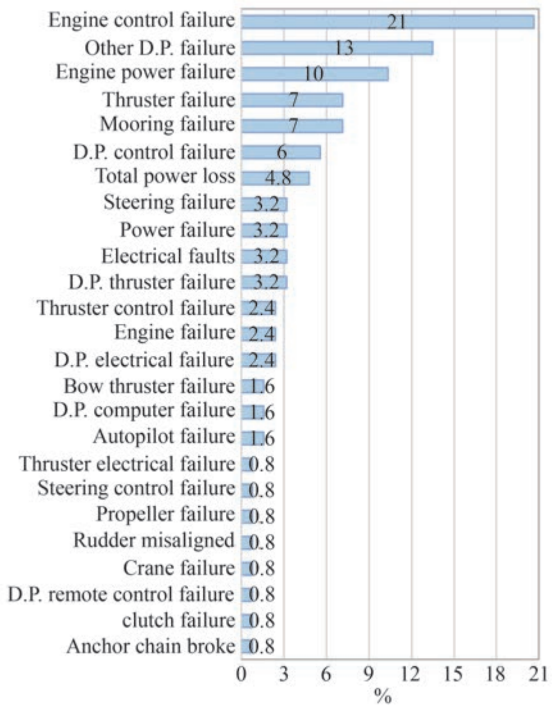

Figure 7 Basic causes of equipment failure

The other two crucial causal factors, *external factors* and *human errors*, are analysed for the basic causes. In both cases, a large share of basic causes has been found to be associated with a single cause. Therefore, these are classified further by experts. Figure 8 presents the basic causes, split into two frames, distributed based on observed data (Data) and expert elicitation (Expert).

As shown in Figure 8(a), external factors are the primary cause of events resulting from adverse weather conditions (82%), followed by anchors being dragged (16%) and obscured vision (2%).

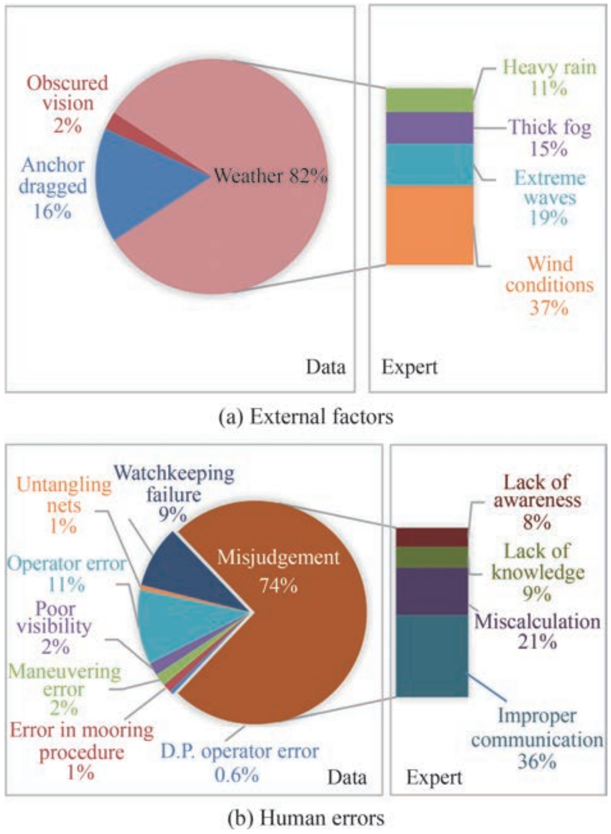

Figure 8 Basic causes

The distribution of common human errors involved in allision incidents is depicted in Figure 8(b). Three-fourths of the errors come under misjudgments, while other significant ones are operator error (11%) and watchkeeping failure (9%). Following the above scheme, misjudgments are further classified as lack of awareness, lack of knowledge, miscalculation and improper communication. Future research will extend the current framework to more precisely identify the nature of errors and root causes through a secondary level of analysis.

3.2 Estimation of the prior probabilities of basic causes

This section primarily builds upon the results from the previous study, focusing on the key inputs for the present approach. As summarized in Section 2.1 and further detailed in Bhardwaj et al. (2024), the main input for the calculation of prior probabilities is annual allision frequency data.

From the analysis conducted in section 3.1, the basic causes are ranked from most important to least important based on the occurrence in the dataset. Table 3 presents the rankings of basic causes.

For the sake of simplicity in the analysis, a smaller set of annual allision frequency data is gathered from the HSE (Loughney et al., 2019), as shown in Table 2. It is to be noted that the last 16-year evidential data is used here to keep calculations simple and as adopted in Bhardwaj et al. (2024). The annual occurrence rate is found by comparing the number of allision incidents reported with the number of installations operating in that year.

Table 2 Number of allision incidents and installations from 2000 to 2015, according to Loughney et al. (2019)

t	Year	Number of allision incidents (A^t)	Number of installations (I^t)	Annual occurrence rate (N^t)
1	2000	18	300	0.060
2	2001	12	307	0.039
3	2002	10	308	0.032
4	2003	6	311	0.019
5	2004	4	313	0.013
6	2005	7	314	0.022
7	2006	8	315	0.025
8	2007	12	331	0.036
9	2008	8	337	0.024
10	2009	4	338	0.012
11	2010	5	332	0.015
12	2011	7	332	0.021
13	2012	4	335	0.012
14	2013	6	337	0.018
15	2014	4	340	0.012
16	2015	3	331	0.009

Based on the rationale that the annual allision occurrence rate (N_t) can be distributed among all identified basic causes ($h = 1, 2, \cdots, 42$), the corresponding annual contributing occurrence rates (λ_h^t, $h = 1, 2, \cdots, 42$, $t = 1, 2, \cdots, 16$) are defined as follows

$$\lambda_1^t + \lambda_2^t + \lambda_3^t + \cdots \lambda_{42}^t = N^t \tag{4}$$

The equation above applies to time t and can be expressed in normalized form as follows

$$\frac{\lambda_1^t}{N^t} + \frac{\lambda_2^t}{N^t} + \frac{\lambda_3^t}{N^t} + \cdots \frac{\lambda_{42}^t}{N^t} = 1 \tag{5}$$

The left-hand ratio is independent of time and reflects the normalized contribution of each basic cause to the overall occurrence of the final event. There can be multiple ways to deduce these weights, such as through the results of simple statistical analysis. Nonetheless, this study builds upon the expert-based methodology employing the DCM, as detailed in the preceding research (Bhardwaj et al., 2024), which implies

$$w(l_1) + w(l_2) + w(l_3) + \cdots w(l_{42}) = \frac{\lambda_1^t}{N^t} + \frac{\lambda_2^t}{N^t} + \frac{\lambda_3^t}{N^t} + \cdots \frac{\lambda_{42}^t}{N^t} = 1 \tag{6}$$

where $w(l_h)$ is the weight deduced from DCM for a basic cause (l_h).

For the given weights $w(l_h)$ from the previous study (Bhardwaj et al., 2024), and the annual occurrence rates (N^t) from Table 2, occurrence rate contributed by each cause for each year can be determined as follows $\lambda_h^t = w(l_h) \times N^t$. Some steps of the estimations of this section are shown in Appendix A.

Across 16 years, contributing occurrence rates for each basic cause were calculated and analyzed using Hierarchical Bayesian Analysis (HBA). The analysis resulted in posterior predictive distributions of the basic event occurrence frequencies, which can be regarded as prior probabilities of their occurrence. The complete results are presented in the last column of Table 3. Thereby, the prior probabilities of basic causes are calculated using evidential data, DCM and HBA.

3.3 BN allision model

The initial process in section 3.1 identifies basic causal factors that are included in the risk assessment of allision accidents. The purpose is to construct a hierarchical representation of the risk-influencing factors underlying allision accident scenarios. The information is used to relate the allision, the intermediate and the basic causes. After understanding the incident's causation, a directed acyclic graph (DAG) BN model is structured based on the structure and relationship among the contributory parameters. The BN model in this study is built using GeNIe (Langseth et al., 2009; Langseth and Portinale, 2007) software developed by the Decision Systems Laboratory at the University of Pittsburgh.

Figure 9 presents the probabilistic allision model. Furthermore, consequences are also modelled. The framework consists of 42 root nodes indicating the basic causes of the allision accident. In the investigation reports, the basic cause is recorded as the last identified factor. While this may not always be the actual root cause, it may still be influenced by deeper contributory factors. For the purpose of this study, the final listed cause is assumed to be the basic cause.

Intermediate nodes represent the principal causal factors and intermediate causes. Figure 9 shows the BN allision model with green nodes identified by expert knowledge. It is important to highlight that the model incorporates only the factors that were actually observed in accident reports, along with those considered most probable based on expert judgement.

After establishing the qualitative framework, the model must be quantified by defining states and assigning probabilities. Each node in the Bayesian Network is given two states "T" for True (present) and "F" for False (absent) to indicate whether a particular causal factor exists.

Table 3 Probability for basic causes from Bhardwaj et al. (2024)

Basic causes	Ranking	Probability × 10^{-4}
D.P. Operator error	1	2.27
Untangling nets	2	2.40
Anchor chain broke	3	2.61
Clutch failure	4	2.83
Crane failure	5	2.98
D.P. Remote control failure	6	3.07
Propeller failure	7	3.19
Rudder misaligned	8	3.40
Steering control failure	9	3.54
Thruster electrical failure	10	3.68
Obscured vision	11	3.77
Error in mooring procedure	12	3.91
Autopilot failure	13	4.11
Bow thruster failure	14	4.17
D.P. Computer failure	15	4.32
Manoeuvring error	16	4.47
Poor visibility	17	4.67
D.P. Electrical failure	18	4.80
Engine failure	19	4.99
Thruster control failure	20	5.29
D.P. Thruster failure	21	5.42
Electrical faults	22	5.51
Power failure	23	5.71
Steering failure	24	5.92
Total power loss	25	5.99
D.P. Control failure	26	6.21
Heavy rain	27	6.33
Mooring failure	28	6.62
Thruster failure	29	6.76
Thick fog	30	6.96
Anchor dragged	31	7.25
Engine power failure	32	7.32
Lack of awareness	33	7.47
Watchkeeping failure	34	7.61
Lack of knowledge	35	7.67
Extreme waves	36	7.88
Other DP failure	37	7.99
Operator error	38	8.16
Engine control failure	39	8.38
Wind conditions	40	8.67
Miscalculation	41	8.99
Improper communication	42	9.47

The prior probabilities applied in the model were obtained from the evaluation detailed earlier and are presented in Table 3. For the node D.P. Operator Error, the probability of occurrence is 2.24×10^{-4}, which is fed to BN as T = 2.24×10^{-4} and F = $1 - 2.24 \times 10^{-4}$. Similarly, all root nodes are assigned probabilities of occurrence and non-occurrence of associated basic cause.

A key aspect of this BN model is the computation of conditional probability tables (CPTs). To minimise complexity, Noisy-OR gates (Langseth et al., 2009; Langseth and Portinale, 2007) are applied at the intermediate nodes, while a simple OR gate is used for the final event, allision.

If interdependencies among failure causes need to be represented, more advanced CPT formulations such as those presented in Adedigba et al. (2016) may be consulted. This study focuses on constructing a practical allision scenario using realistic, although limited, data. The authors do not claim absolute numerical precision; the model can be refined as more data become available, serving both qualitative and quantitative purposes.

The probability of allision is estimated as 3.40×10^{-3}, while the probabilities of various consequence classes are calculated as 7.48×10^{-3} for None, 2.13×10^{-3} for Minor 4.11×10^{-4} for Moderate and 1.05×10^{-4} for Severe.

3.4 Sensitivity analysis model

A key component of BN analysis is identifying the most influential input parameters through sensitivity analysis. Its purpose is to evaluate how variations in the input parameters affect a selected model output. This step is essential in risk assessment, as it helps determine model robustness and supports model validation (Tarantola et al., 2007). The simplest form of sensitivity is expressed as the partial derivative of an output with respect to an input parameter, which represents a local sensitivity measure, since it is evaluated at a specific point within the input space.

Another important approach for assessing model properties and robustness is sensitivity to evidence. This method examines changes in the posterior probability distribution of the BN under different conditions, typically using entropy or mutual information (also termed variance reduction for continuous variables). Based on this approach, a sensitivity metric is adopted in this study as follows.

The change in the probability of basic events (variable Y_i) from prior to posterior is measured when the target node (final event) is fixed to a 100% occurrence. This variation is expressed as a change ratio (CR_{Y_i}) given by:

$$\mathrm{CR}_{Y_i} = \left(\frac{\Pr(100\%) - \text{Prior probability of } Y_i}{\text{Prior probability of } Y_i} \right) \tag{7}$$

Where Pr (100%) is the probability of Y_i after setting the final event to 100%.

The overall influence of variable Y_i on the final event is

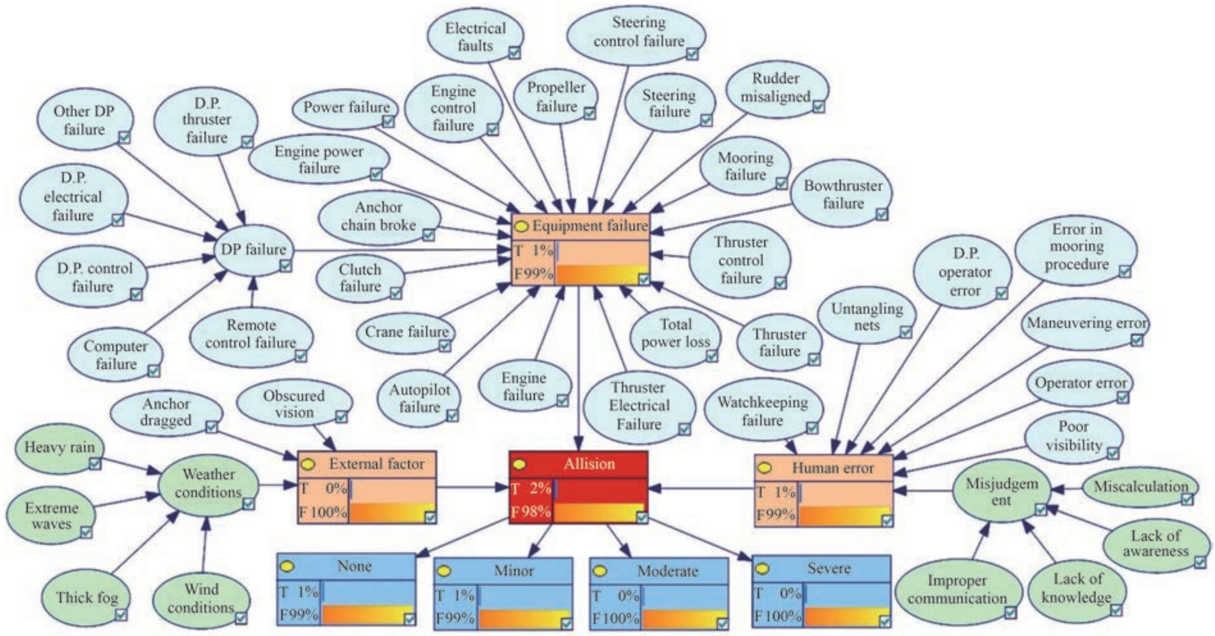

Figure 9 BN model for allision accident (consequences are represented by blue nodes, immediate causes by orange nodes, and assumed factors by green nodes)

quantified by a global sensitivity index, calculated from the change ratio as follows:

$$S_{Y_i} = \frac{\mathrm{CR}_{Y_i}}{\sqrt{\sum_{i=1}^{m}\left(\mathrm{CR}_{Y_i}\right)^2}} \tag{8}$$

A sensitivity analysis is also performed to investigate how the root node probability would affect the final node. The final event "Allision" is set to True = 100%, indicating its occurrence, and the basic causes now correspond to the posterior probabilities. Figure 10 shows the BN when the allision event is set to 100%. The posterior probability values are used to calculate the sensitivity factors S_{Y_i} of the variables as per Eqs. (7) and (8). The results of the sensitivity analysis are presented in Table 4.

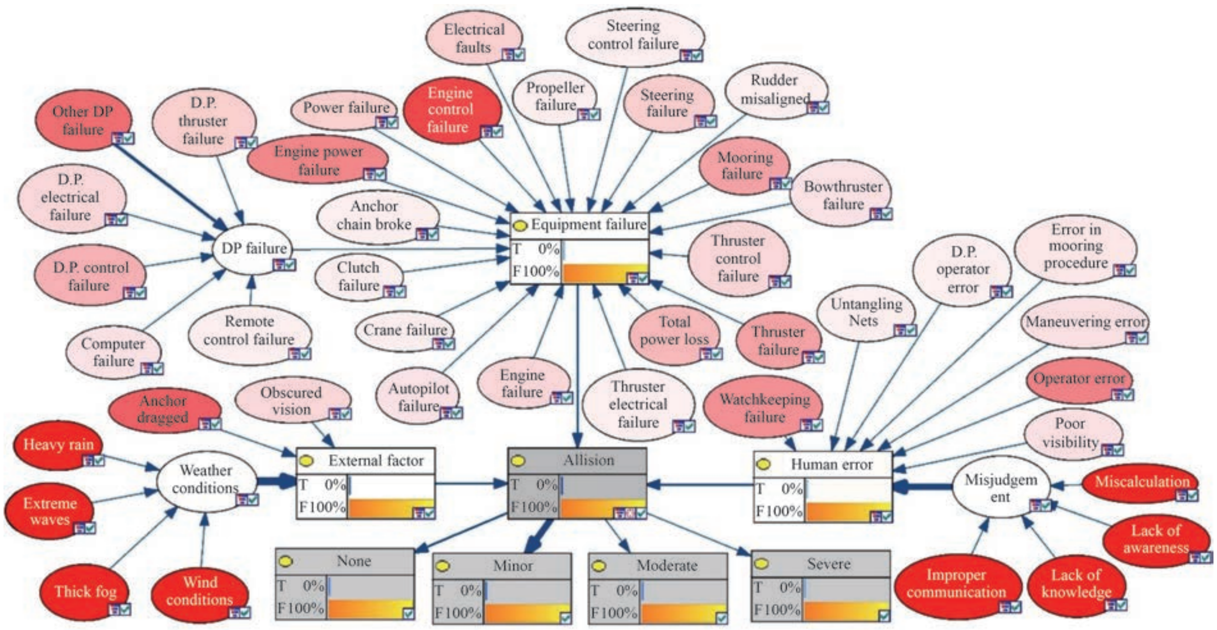

Figure 10 BN when evidence is set to allision (The relative importance of the causes is illustrated using varying intensities of red, with deeper shades representing higher significance)

Table 4 Number of allision incidents and installations

Basic causes	*Pr (BC)| Pr (allision) = 100%) × 10^{-3}	Sensitivity factors in %
D.P. Operator error	0.62	0.13
Untangling nets	0.66	0.13
Anchor chain broke	0.87	0.18
Clutch failure	0.94	0.18
Crane failure	0.98	0.18
D.P. Remote control Failure	0.99	0.17
Propeller failure	1.05	0.18
Rudder misaligned	1.12	0.18
Steering control failure	1.17	0.18
Thruster electrical failure	1.22	0.18
Obscured vision	2.98	0.53
Error in mooring procedure	1.74	0.26
Autopilot failure	2.31	0.35
Bow thruster failure	2.35	0.35
D.P. Computer failure	2.42	0.35
Manoeuvring error	2.76	0.40
Poor visibility	2.89	0.40
D.P. Electrical failure	3.78	0.52
Engine failure	3.98	0.53
Thruster control failure	4.21	0.53
D.P. Thruster failure	5.56	0.70
Electrical faults	5.65	0.70
Power failure	5.87	0.70
Steering failure	6.08	0.70
Total power loss	8.94	1.05
D.P. Control failure	10.62	1.22
Heavy rain	75.73	8.95
Mooring failure	14.30	1.56
Thruster failure	14.61	1.56
Thick fog	83.30	8.95
Anchor dragged	34.20	3.49
Engine power failure	22.63	2.26
Lack of awareness	81.13	8.14
Watchkeeping failure	20.62	1.97
Lack of knowledge	83.42	8.14
Extreme waves	94.21	8.95
Other DP failure	32.25	2.96
Operator error	26.42	2.37
Engine control failure	50.94	4.52
Wind conditions	103.45	8.95
Miscalculation	97.94	8.14
Improper communication	103.29	8.14

* Pr (BC)| Pr (allision) = 100%) – Probability of basic causes when "Allision" is set to True = 100%

A sensitivity analysis is provided in Figure 10, which shows the node changes maximum in the sensitivity analysis. The colour changes indicate more visual relative sensitivity.

The causes related to weather, such as heavy rain, extreme waves, wind conditions, and thick fog, have the greatest effect, making the allision probability worse by a power of two.

The second group of causes that significantly influence the allision probability are miscalculation, improper communication, lack of knowledge and awareness. These causes have a significantly greater influence on the final event compared to other causes, as indicated by the dark red nodes in Figure 10 and the sensitivity values in Table 4. Other important causes are engine control failure, anchor dragged, engine power failure, other DP failure and operator error. The information provided in this section may be useful for decision-makers to prioritize their resources.

4 Conclusions

This study proposes an integrated approach for risk assessment and probabilistic modelling of allision accidents of vessels with offshore installations.

The methodology consists of data collection and analysis, development of a causal framework, and estimation of prior probabilities as the main steps. Data is collected from UK Health and Safety Executives describing allision accidents around the UK continental shelf. Further sources of allision accidents are consulted to understand the causation phenomenon. The following are some key findings from the statistical analysis of the data.

- Supply vessels account for 61% of involvement in allision incidents;
- allision happening in a type of vessel is specific to the month of the year;
- most of the incidents are developed during cargo transfer (23%), approaching installation (18.5%) and cargo unloading (11%);
- fixed installations account for 48% of incidents while Semi-submersible drilling units are involved in 27% of the incidents;
- 3% of incidents are escalated to severe accidents, 10% are moderate and 53% of them are minor incidents.

The result of causal analysis revealed that the main contributors to accidents are human errors (30%), followed by equipment failures (22%) and external factors (15%). The next layer of analysis identified the basic causes and last identified causes in the datasets.

By the application of Bayesian networks, the causal network is framed, representing the main event as an allision accident, intermediate causes and basic causes. The issue of prior probabilities of basic causes is addressed using a novel technique that synthesises historical data and an expert's subjective knowledge.

Some insights for the allision risk model are provided via probabilistic analysis. Finally, a sensitivity analysis is conducted, which suggests that weather-related causes, such as heavy rain, extreme waves, wind conditions, and thick fog, have the greatest effect on allision probability.

This study addresses data scarcity and reporting bias by developing a BN model that also incorporates consequence nodes. Despite its value, limitations remain: human error is dominant yet still underrepresented, and the model requires more data for robust representation. Moreover, BNs are not universally transferable and must be calibrated to regional conditions. Future work will integrate temporal variability, AIS data, near-miss reports, and simulation outputs to mitigate underreporting, while hybrid BN models combined with human reliability analysis will be explored to enhance predictive capacity and practical applicability.

The present methodology provides much detailed information about allision scenarios for the stakeholders in the offshore sector, which is useful in policy-making to ensure safety.

Appendix A

1 Application of DCM

There are 42 identified basic causes, which are ranked in consecutive levels l_1 to l_{42} (where l1 corresponds to the least important cause and vice versa) based on the number of occurrences in databases. The number of blank cards is placed between two consecutive levels (say "1" between l_1 and l_2 $\cdots$. say "6" between l_{41} and l_{42}) in the comparison table, while rest of the entries are filled using the consistency condition (Corrente et al., 2021b). The end result of this analysis yields the relative weight of basic causes- $w\left(l_2\right)$, $w\left(l_3\right) \cdots w\left(l_{42}\right)$ which are estimated as 0.0103, 0.0112, $\cdots$ 0.0409, respectively.

Table A1 Comparison table

	l_1	l_2	l_3	l_4	.	.	l_{42}
l_1		**1**	4	7			102
l_2			**2**	5			100
l_3				**2**			97
.					.		
.						.	
l_{41}							**6**
l_{42}							

2 Estimation of the occurrence rate of basic causes (λ_h^t, h = 1 to 42 basic causes)

If N^t be the annual occurrence rate of allision, the annual contributing occurrence rates can be calculated for each cause per year as $\lambda_h^t = w\left(l_h\right) \times N^t$.

Table A2 Annual contributing occurrence rates for all the basic causes

t	λ_1^t	λ_2^t	λ_3^t	$\cdots$	λ_{42}^t
1	5.84×10^{-4}	6.20×10^{-4}	6.74×10^{-4}		2.45×10^{-3}
2	3.80×10^{-4}	4.04×10^{-4}	4.39×10^{-4}		1.60×10^{-3}
3	3.16×10^{-4}	3.35×10^{-4}	3.65×10^{-4}		1.33×10^{-3}
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15	1.14×10^{-4}	1.22×10^{-4}	1.32×10^{-4}		4.81×10^{-4}
16	8.82×10^{-5}	9.36×10^{-5}	1.02×10^{-4}		3.70×10^{-4}

3 Estimation of probability of occurrence using HBA

The probability of a basic cause (θ^t) can be derived from contributing occurrence rates (λ_h^t, h = 1 to 42 basic causes, t = 1 to 16 years) observed against time using the HBA. The θ^t is considered to follow a gamma distribution with α and β being its hyperparameters, that is $\theta^t \sim$ gamma (α, β). Furthermore, hyperparameters are also assumed diffusive gamma distribution as $\alpha \sim$ gamma (0.000 1, 0.000 1) and $\beta \sim$ gamma (0.000 1, 0.000 1).

Assuming the basic causes to be an event-based process and thus, the contributing occurrence rates in each time interval (year) follow a Poisson distribution as $\lambda^t \sim$ Poisson (θ^t, t). The corresponding values of λ^t for each basic cause are listed in Table A2.

The corresponding estimations are done in OpenBugs which uses Markov Chain Monte Carlo simulations. Figure A2 illustrates the posterior distribution $\bar{\theta}$ inferred as probability density function of a sample basic cause–Untangling nets (i.e. h = 2).

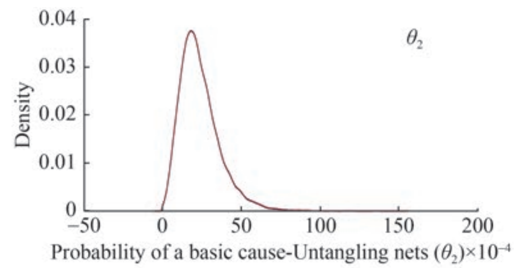

Figure A1 Posterior distribution ($\bar{\theta}_2$) of basic cause–Untangling nets

Table A3 Probability for basic causes from (Bhardwaj et al., 2024)

Basic causes	Rank (l_h)	$w(l_h)$	Probability × 10^{-4}
D.P. Operator error	l_1	0.0097	2.27
Untangling nets	l_2	0.0103	2.40
Anchor chain broke	l_3	0.0112	2.61
Clutch failure	l_4	0.0121	2.83
Crane failure	l_5	0.0127	2.98
D.P. Remote control failure	l_6	0.0131	3.07
Propeller failure	l_7	0.0137	3.19
Rudder misaligned	l_8	0.0146	3.40
Steering control failure	l_9	0.0152	3.54
Thruster electrical failure	l_{10}	0.0158	3.68
Obscured vision	l_{11}	0.0161	3.77
Error in mooring procedure	l_{12}	0.0167	3.91
Autopilot failure	l_{13}	0.0176	4.11
Bow thruster failure	l_{14}	0.0179	4.17
D.P. Computer failure	l_{15}	0.0185	4.32
Manoeuvring error	l_{16}	0.0191	4.47
Poor visibility	l_{17}	0.0200	4.67
D.P. Electrical failure	l_{18}	0.0206	4.80
Engine failure	l_{19}	0.0215	4.99
Thruster control failure	l_{20}	0.0227	5.29
D.P. Thruster failure	l_{21}	0.0233	5.42
Electrical faults	l_{22}	0.0236	5.51
Power failure	l_{23}	0.0245	5.71
Steering failure	l_{24}	0.0254	5.92
Total power loss	l_{25}	0.0257	5.99
D.P. Control failure	l_{26}	0.0267	6.21
Heavy rain	l_{27}	0.0273	6.33
Mooring failure	l_{28}	0.0285	6.62
Thruster failure	l_{29}	0.0291	6.76
Thick fog	l_{30}	0.0300	6.96
Anchor dragged	l_{31}	0.0312	7.25
Engine power failure	l_{32}	0.0315	7.32
Lack of awareness	l_{33}	0.0321	7.47
Watchkeeping failure	l_{34}	0.0327	7.61
Lack of knowledge	l_{35}	0.0330	7.67
Extreme waves	l_{36}	0.0339	7.88
Other DP failure	l_{37}	0.0345	7.99
Operator error	l_{38}	0.0351	8.16
Engine control failure	l_{39}	0.0360	8.38
Wind conditions	l_{40}	0.0372	8.67
Miscalculation	l_{41}	0.0387	8.99
Improper communication	l_{42}	0.0409	9.47

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References

Adedigba SA, Khan F, Yang M (2016) Process accident model considering dependency among contributory factors. Process Safety and Environmental Protection 102: 633-647. https://doi.org/10.1016/j.psep.2016.05.004

Almeida AG de, Vinnem JE (2020) Major accident prevention illustrated by hydrocarbon leak case studies: A comparison between Brazilian and Norwegian offshore functional petroleum safety regulatory approaches. Safety Science 121: 652-665. https://doi.org/10.1016/j.ssci.2019.08.028

Amin Md T, Khan F, Imtiaz S (2018) Dynamic availability assessment of safety critical systems using a dynamic Bayesian network. Reliability Engineering & System Safety 178: 108-117. https://doi.org/10.1016/j.ress.2018.05.017

Bayazit O, Kaptan M (2024) Dynamic risk analysis of allision in port areas using DBN based on HFACS-PV. Ocean Engineering 298: 117183. https://doi.org/10.1016/j.oceaneng. 2024.117183

Bhardwaj U, Teixeira AP, Guedes Soares C (2017) Analysis of FPSO accident and incident data. In: Guedes Soares C and Garbatov Y (eds) Progress in the Analysis and Design of Marine Structures, Taylor & Francis Group, London, pp 773-782.

Bhardwaj U, Teixeira AP, Guedes Soares C (2018) Availability assessment of a power plant working on the Allam cycle. In Guedes Soares C and Santos TA (eds) Progress in Maritime Technology and Engineering, Taylor & Francis Group, London, pp 525-536. https://doi.org/10.1201/9780429505294-60

Bhardwaj U, Teixeira AP, Guedes Soares C (2022a) Bayesian framework for reliability prediction of subsea processing systems accounting for influencing factors uncertainty. Reliability Engineering and System Safety 218: 108143. https://doi.org/10.1016/j.ress.2021.108143

Bhardwaj U, Teixeira AP, Guedes Soares C (2022b) Casualty analysis methodology and taxonomy for FPSO accident analysis. Reliability Engineering and System Safety 218: 108169. https://doi.org/10.1016/j.ress.2021.108169

Bhardwaj U, Teixeira AP, Guedes Soares C (2024) Probabilistic Analysis of Basic Causes of Vessel–Platform Allision Accidents. Journal of Marine Science and Engineering 12(3): 390. https://doi.org/10.3390/jmse12030390

Bhardwaj U, Teixeira AP, Guedes Soares C, Ariffin AK, Singh SS (2021) Evidence based risk analysis of Fire and Explosion accident scenarios in FPSOs. Reliability Engineering & System Safety 215: 107904. https://doi.org/10.1016/j.ress.2021.107904

BSEE (2023) Offshore Incident Statistics. Bureau of Safety and Environmental Enforcement. https://www. bsee. gov/stats-facts/offshore-incident-statistics

Cai B, Liu Y, Liu Z, Tian X, Dong X, Yu S (2012) Using Bayesian networks in reliability evaluation for subsea blowout preventer control system. Reliability Engineering & System Safety 108: 32-41. https://doi.org/10.1016/j.ress. 2012.07.006

Ceylan BO, Akyuz E, Arslan O (2021) Systems-Theoretic Accident Model and Processes (STAMP) approach to analyse socio-technical systems of ship allision in narrow waters. Ocean Engineering 239: 109804. https://doi.org/10.1016/j.oceaneng.2021.109804

Chen H, Moan T (2004) Probabilistic modeling and evaluation of collision between shuttle tanker and FPSO in tandem offloading. Reliability Engineering & System Safety 84(2): 169-186. https://doi.org/10.1016/j.ress.2003.10.015

Christou M, Konstantinidou M (2012) Safety of offshore oil and gas operations: Lessons from past accident analysis. In JRC scientific and policy reports. European Commission Joint Research Centre Institute for Energy and Transport. https://doi.org/10.2790/73321

Čorić M, Mandžuka S, Gudelj A, Lušić Z (2021) Quantitative Ship Collision Frequency Estimation Models: A Review. In Journal of Marine Science and Engineering 9(5): 533. https://doi.org/10.3390/jmse9050533

Corrente S, Figueira JR, Greco S (2021a) Pairwise comparison tables within the deck of cards method in multiple criteria decision aiding. European Journal of Operational Research 291(2): 738-756. https://doi.org/10.1016/j.ejor.2020.09.036

Corrente S, Figueira JR, Greco S (2021b) Pairwise comparison tables within the deck of cards method in multiple criteria decision aiding. European Journal of Operational Research 291(2): 738-756. https://doi.org/10.1016/j.ejor.2020.09.036

eMARS (2023) Major Accident Reporting System. https://emars.jrc.ec.europa.eu/en/emars/content

EMSA (2023) European Marine Casualty Information Platform–EMCIP. https://portal. emsa. europa. eu/emcip-public/#/public-occurrences

Fan S, Blanco-Davis E, Yang Z, Zhang J, Yan X (2020) Incorporation of human factors into maritime accident analysis using a data-driven Bayesian network. Reliability Engineering & System Safety 203: 107070. https://doi.org/10.1016/j.ress.2020.107070

Figueira J, Roy B (2002) Determining the weights of criteria in the ELECTRE type methods with a revised Simos' procedure. European Journal of Operational Research 139(2): 317-326. https://doi.org/10.1016/S0377-2217(01)00370-8

Geijerstam K af, Svensson H (2008) Ship Collision Risk -An identification and evaluation of important factors in collisions with offshore installations [Lund University, Sweden]. In Encyclopedia of Maritime and Offshore Engineering. https://doi. org/10.1002/9781118476406.emoe 357

Graziano A, Teixeira AP, Guedes Soares, C (2016) Classification of human errors in grounding and collision accidents using the TRACEr taxonomy. Safety Science 86: 245-257. https://doi. org/10.1016/j.ssci.2016.02.026

Hassel M, Utne IB, Vinnem JE (2021) An allision risk model for passing vessels and offshore oil and gas installations on the Norwegian Continental Shelf. Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability 235(1): 17-32. https://doi.org/10.1177/1748006X 20957481

Haugen S (1991) Probabilistic evaluation of frequency of collision between ships and offshore platforms. Norwegian University of Science and Technology, Trondheim, Norway.

Haugen SKL VF (1994) COLLIDE–collision design criteria, phase II–Reference manual.

Haugen S, Moan T (1992) Frequency of collision between ships and platforms. OMAE, 11th Intl Conf on Offshore Mechanics & Arctic Engg, p 359.

Hörteborn A, Ringsberg JW (2021) A method for risk analysis of ship collisions with stationary infrastructure using AIS data and a ship manoeuvring simulator. Ocean Engineering 235: 109396. https://doi.org/10.1016/j.oceaneng.2021.109396

Hörteborn A, Ringsberg JW, Lundbäck O, Mao W (2025) Probabilistic analysis of ship-bridge allisions when designing bridges. Reliability Engineering & System Safety 260: 111026. https://doi.org/10.1016/j.ress.2025.111026

HSE Books (2017) Offshore accident and failure frequency data sources-review and recommendations RR1114. Health and Safety Executive.

HSE (2023) Offshore Statistics & Regulatory Activity Report 2022. Health and Safety Executive. www.hse.gov.uk/offshore/statistics.htm

IEC 31010 (2019) Risk management-Risk assessment techniques.

Kaptan M, Bayazit O (2024) Data-driven Bayesian risk assessment of factors influencing the severity of marine accidents in port areas. Process Safety and Environmental Protection 192: 1094-1109. https://doi.org/10.1016/j.psep.2024.10.074

Kelly DL, Smith CL (2009) Bayesian inference in probabilistic risk assessment—The current state of the art. Reliability Engineering & System Safety 94(2): 628-643. https://doi.org/10.1016/j.ress.2008.07.002

Khakzad N, Khan F, Amyotte P (2011) Safety analysis in process facilities: Comparison of fault tree and Bayesian network approaches. Reliability Engineering & System Safety 96: 925-932. https://doi.org/10.1016/j.ress.2011.03.012

Khakzad N, Khan F, Amyotte P (2013) Risk-based design of process systems using discrete-time Bayesian networks. Reliability Engineering System Safety 109: 5-17. https://doi. org/10.1016/j. ress. 2012.07.009

Khakzad N, Reniers G (2018) Safety of offshore topside processing facilities: The era of FPSOs and FLNGs. In Offshore Process Safety (1st ed, Vol 2, pp 269-287). Elsevier Inc. https://doi. org/10.1016/bs.mcps.2018.04.004

Langseth H, Nielsen TD, Rumí R, Salmerón A (2009) Inference in hybrid Bayesian networks. Reliability Engineering & System Safety 94(10): 1499-1509. https://doi.org/10.1016/j.ress.2009.02.027

Langseth H, Portinale L (2007) Bayesian networks in reliability. Reliability Engineering & System Safety 92(1): 92-108. https://doi.org/10.1016/j.ress.2005.11.037

Li KX, Yin J, Bang HS, Yang Z, Wang J (2014) Bayesian network with quantitative input for maritime risk analysis. Transportmetrica A: Transport Science 10(2): 89-118. https://doi. org/10.1080/18128602.2012.675527

Liu K, Yu Q, Yuan Z, Yang Z, Shu Y (2021) A systematic analysis for maritime accidents causation in Chinese coastal waters using machine learning approaches. Ocean & Coastal Management 213: 105859. https://doi.org/10.1016/j. ocecoaman.2021.105859

Loughney S, Wang J, Wall A (2019) Ship/Platform Collision Incident Database (2015) for offshore oil and gas installations. In HSE

Books (RR1154 ed). Health and Safety Executive.
MAIB (2023) Marine Accident Investigation reports. (Marine Accident Investigation Branch). https://www.gov.uk/maib-reports
Mujeeb-Ahmed MP, Seo JK, Paik JK (2018) Probabilistic approach for collision risk analysis of powered vessel with offshore platforms. Ocean Engineering 151: 206-221. https://doi.org/10.1016/j.oceaneng.2018.01.008
Norazahar N, Khan F, Veitch B, MacKinnon S (2014) Human and organizational factors assessment of the evacuation operation of BP Deepwater Horizon accident. Safety Science 70: 41-49. https://doi.org/10.1016/j.ssci.2014.05.002
Norwegian Ocean Industry Authority (Havtil) (2023) Investigation reports. Petroleum Safety Authority. https://www.ptil.no/en/supervision/investigation-reports/
Oltedal HA (2012) Ship-platform collisions in the north sea. European Safety and Reliability Conference 8: 6470-6479
Pedersen PT (2002) Collision risk for fixed offshore structures close to high-density shipping lanes. Proceedings of the Institution of Mechanical Engineers, Part M: Journal of Engineering for the Maritime Environment 216(1): 29-44. https://doi.org/10.1243/147509002320382121
Robson JK (2001) Ship/Platform Collision Incident Database. Serco Assurance, Culham, Abingdon, Oxfordshire, United Kingdom. Report prepared for the Offshore Division of the Health and Safety Executive (HSE), United Kingdom Continental Shelf (UKCS). HSE Books
Silveira PAM, Guedes Soares, C, Teixeira AP (2013) Use of AIS Data to Characterise Marine Traffic Patterns and Ship Collision Risk off the Coast of Portugal. Journal of Navigation 66(6): 879-898. https://doi.org/10.1017/S03734 63313000519
Son WJ, Cho IS (2024) Optimal maritime traffic width for passing offshore wind farms based on ship collision probability. Ocean Engineering 313: 119498. https://doi.org/10.1016/j.oceaneng.2024.119498
Song G, Khan F, Wang H, Leighton S, Yuan Z, Liu H (2016) Dynamic occupational risk model for offshore operations in harsh environments. Reliability Engineering & System Safety 150: 58-64. https://doi.org/10.1016/j.ress.2016.01.021
Spouge J (2017) Storage Tank Explosion Frequencies on FPSOs. Hazards 162: 1-5
Tarantola A, Ratto M, Andres T, Campolongo F, Cariboni J, Gatelli D, Saisana M, Tarantola S (2007) Introduction to sensitivity analysis. In Global Sensitivity Analysis. The Primer (pp 1-51). John Wiley & Sons, Ltd. https://doi.org/10.1002/9780 470725184
UK Oil and Gas (2010) Guidelines for Ship/Installation Collision Avoidance (Issue 2). United Kingdom Offshore Oil and Gas Industry Association Limited. https://doi.org/10.1007/1-4020-0613-6_2971
USCG (2023) Marine Casualty Reports (United States Coast Guard). https://www.dco.uscg.mil/Our-Organization/Assista nt-Commandant-for-Prevention-Policy-CG-5P/Inspections-Compliance-CG-5PC-/Office-of-Investigations-Casualty-Analysis/Marine-Casualty-Reports/
van der Tak C, Glansdorp CC (1995) Ship offshore platform collision risk assessment (SOCRA). 5th International Conference on Loss Prevention in the Oil and Gas Industry
Wang B, Zhu S, Hao P, Bi X, Du K, Chen B, Ma X, Chao YJ (2018) Buckling of quasi-perfect cylindrical shell under axial compression: A combined experimental and numerical investigation. International Journal of Solids and Structures 130-131: 232-247. https://doi.org/10.1016/j.ijsolstr.2017.09.029
Xiao F, Ma Y, Wu B (2022) Review of Probabilistic Risk Assessment Models for Ship Collisions with Structures. In Applied Sciences (Vol. 12, Issue 7). https://doi.org/10.3390 /app12073441
Yin B, Li B, Liu G, Wang Z, Sun B (2021) Quantitative risk analysis of offshore well blowout using bayesian network. Safety Science 135: 105080. https://doi.org/10.1016/j.ssci.2020.105080
Zhang D, Yan XP, Yang ZL, Wall A, Wang J (2013) Incorporation of formal safety assessment and Bayesian network in navigational risk estimation of the Yangtze River. Reliability Engineering & System Safety 118: 93-105. https://doi.org/10.1016/j.ress.2013.04.006
Zhang J, Teixeira ÂP, Guedes Soares C, Yan X, Liu K (2016) Maritime Transportation Risk Assessment of Tianjin Port with Bayesian Belief Networks. Risk Analysis 36(6): 1171-1187. https://doi.org/https://doi.org/10.1111/risa.12519
Zhao J, Price WG, Wilson PA (1994) Risk assessment of ship/platform collision. Marine, Offshore and Ice Technology 5: 187-194. Computational Mechanics.
Zhen X, Ning Y, Du W, Huang Y, Vinnem JE (2023) An interpretable and augmented machine-learning approach for causation analysis of major accident risk indicators in the offshore petroleum industry. Process Safety and Environmental Protection 173: 922-933. https://doi.org/10.1016/j.psep.2023.03.063