Evaluating the Safety of Port-to-Ship Liquefied Hydrogen Bunkering Through Fault Tree Analysis and Fuzzy Bayesian Networks

Dwitya Harits Waskito[1,2], Ayudhia Pangestu Gusti[2], Ludfi Pratiwi Bowo[2], Prastya Rizky Ramadhan[2], Wirya Sarwana[3,4]

As marine fuels transition toward zero carbon dioxide emissions, hydrogen emerges as a promising alternative due to its near-zero emissions and high energy density. However, hydrogen's high flammability presents a significant risk of fire-related accidents onboard ships. Among the various operations involving hydrogen in the maritime sector, bunkering is one of the most critical. This process carries risks such as leakage, pressure failures, and human errors, which can lead to severe consequences. This study analyzes the safety of the liquefied hydrogen bunkering process. Fault Tree Analysis (FTA) was used to identify failures within the bunkering system, employing a top-down approach that traces failures from the top event to the basic events. Fuzzy Set Theory was applied to quantify risk by aggregating linguistic variables from five experts to estimate the probabilities of basic events. Bayesian Networks (BN) were then used to establish causal relationships between factors and identify the minimum cut sets leading to the top event of bunkering failure. Rate of Variation (RoV) analysis of the posterior probabilities of basic events revealed that human error, particularly due to task execution problems and human-machine interface issues, is the most significant factor influencing bunkering failures. The findings highlight critical areas that require attention to enhance the safety of liquefied hydrogen bunkering operations in the maritime sector, especially for relevant stakeholders.

KEYWORDS
~ Hydrogen
~ Bunkering
~ Fuzzy Bayesian network
~ Fault tree
~ Leakage

[1] University of Strathclyde, Glasgow, United Kingdom
[2] National Research and Innovation Agency - Research Centre for Transportation Technology, South Tangerang, Indonesia
[3] King Fahd University of Petroleum and Minerals, Interdisciplinary Research Center – HTC, Dhahran, Saudi Arabia
[4] National Research and Innovation Agency, Research Centre for Catalysis, South Tangerang, Indonesia
e-mail: dwitya-harits-waskito@strath.ac.uk

doi: 10.7225/toms.v15.n01.001

Received: 6 Mar 2025 / Revised: 20 Oct 2025 / Accepted: 19 Apr 2026 / Published: 20 Apr 2026

1. INTRODUCTION

The global drive for sustainable energy solutions has heightened interest in hydrogen as a clean marine fuel. With its high gravimetric energy density and potential to significantly reduce greenhouse gas emissions, hydrogen is increasingly viewed as a viable option for the shipping sector in meeting the International Maritime Organization's 2050 decarbonization targets (Hosseini & Butler, 2020; Joung et al., 2020). Previous maritime research has examined hydrogen safety at the systems level, including onboard storage and fuel supply, ventilation strategies, emergency response, and lessons transferable from LNG. These studies have clarified generic hazards, flammability, low ignition energy, cryogenic exposure, and organizational factors such as procedures and training (Tsunemi et al., 2019; Hansen, 2020). Liquefied hydrogen (LH_2) in particular enables more efficient storage and transport than gaseous hydrogen, supporting its adoption for maritime applications (Nerheim et al., 2021). However, the safety of storage, transportation, and handling must be carefully addressed to protect port workers, nearby communities, and the environment. The hydrogen liquefaction process is energy-intensive, requiring substantial resources and infrastructure, while transporting and storing LH_2 introduces further logistical and operational complexities due to hydrogen's small molecular size and high reactivity, which necessitate specialized equipment and procedures (Aziz, 2021). Compared to other alternative marine fuels, hydrogen presents a distinct risk profile: LNG shares cryogenic hazards but differs in dispersion and ignition behavior, ammonia offers dense hydrogen carriage but poses acute toxicity concerns, and methanol is easier to store but has low flash points and CO_2 emissions (Abdin et al., 2022; Alavi-Borazjani et al., 2025; Majumdar et al., 2021; Visser et al., 2020). Broader analyses also highlight that while ammonia and methanol are easier to store at ambient conditions, their toxicity and carbon intensity limit their long-term viability, placing hydrogen in a unique position: environmentally attractive but operationally demanding (Cava et al., 2025; Giannis et al., 2023). These contrasts emphasize the need for tailored safety frameworks specific to hydrogen-powered ships.

Building on the recognition of hydrogen's distinct risk profile, researchers have applied various safety analysis methods in maritime contexts. H. Zhang & Jiang (2023) used a Formal Safety Assessment framework with a fuzzy comprehensive evaluation model to quantify fire risks in shipboard hydrogen storage systems. Sumon et al. (2024) utilized Systems-Theoretic Process Analysis to identify unsafe control actions and loss scenarios in hydrogen-driven autonomous vessels, and G. Li et al. (2025) developed a Noisy-OR Bayesian network to estimate leakage probabilities in hydrogen fuel systems. For concept design, risk assessment has been conducted using HyRAM to address risks related to passenger ship safety, based on IGF code requirements (Aarskog et al., 2020). Regarding general risk assessment, an updated FMEA method, integrated with hydrogen databases and accident information, has been used to assess the safety of nine subsystems. The results indicated that the most significant risks are associated with storage tank failures and fuel cell system malfunctions (Ventikos et al., 2023). In summary, existing research demonstrates the utility of causal modelling and probabilistic reasoning in addressing hydrogen-related risks.

Beyond vessel operations, bunkering has emerged as a distinct area of concern, introducing transient and interface-specific risks during port-to-ship transfer. Studies on hydrogen bunkering safety have examined transfer equipment, operational procedures, emergency shutdown systems, detection and zoning, and boil-off gas management (Skiba, 2024). These analyses highlight the importance of robust safety protocols and risk management strategies to address hydrogen's wide flammability range and low ignition energy. However, many investigations treat hydrogen alongside other fuels or focus on compressed H_2 rather than LH_2. As a result, LH_2-specific failure modes, extreme cryogenic temperatures (≈ –253 °C), rapid phase change, material embrittlement, and dispersion in partially enclosed spaces, are not consistently represented at the system level (Adams et al., 2024; Al Ghafri et al., 2022). Compared to ammonia and methanol, which are easier to store at ambient conditions but limited by toxicity and emissions, LH_2 requires specialized insulation, boil-off gas handling, and material compatibility measures (Kang et al., 2023; Mekonnin et al., 2025; H. Wang & Miller, 2016). Effective mitigation strategies such as advanced leak detection, fire suppression, and automated emergency shutdown systems are therefore recognized as essential to safe bunkering operations (Calabrese et al., 2024; Genovese et al., 2024). In terms of risk assessment of hydrogen bunkering, Schiaroli et al. (2024) conducted a preliminary risk analysis to identify the most safety-critical components of LH_2 facilities. Campari et al. (2024) proposed a risk-based inspection framework specifically designed for LH_2 bunkering, emphasizing the prioritization of safety-critical components under cryogenic conditions. While progress has been made, bunkering-focused studies remain fragmented and often lack integration of engineering, operational, and human factors.

One of the most prominent methods to analyses the risk of LH_2 bunkering is by applying structured probabilistic and logic-based approaches to hydrogen safety, including FTA, BN, and Fuzzy Bayesian Networks (FBN). The integrated method is suitable due to its capability to assess failure event within the system and the probabilistic inference update from the BN. In parallel, FBNs have been recognized as a suitable extension of BN for incorporating imprecise and incomplete information, thereby enabling the integration of linguistic expert judgment in safety assessments (Wan et al., 2019; Q. Zhou et al., 2018). The FTA-BN in LH_2 bunkering has been employed to analyses the performance assessment of safety barriers such as release prevention barriers, release detection barriers, and ignition prevention barriers (Tamburini et al., 2024). To complement the study, the system resilience in escalation scenarios has also been conducted by employing FTA and

Dynamic Bayesian Network (DBN) (Tamburini et al., 2025). However, these studies have not explored dynamic or contextual variables such as weather conditions, human factors, and mechanical problems of purging and insulation. Consequently, a comprehensive, system-level applications of FTA and FBN to port-to-ship LH_2 bunkering remain scarce.

Despite growing attention to hydrogen safety in shipping, system-level analyses dedicated specifically to port-to-ship LH_2 bunkering remain scarce. Existing studies are often either fuel-generic or component-focused, overlooking the transient and interface-specific risks that arise during bunkering operations, such as the combined role of shore- and ship-side barriers. Moreover, while FTA has been used to identify failure pathways and BN/FBN to quantify uncertainty, their integrated application to capture dynamic variables, including weather conditions, human factors, and operational deviations, has not yet been established. This leaves a critical gap for a comprehensive probabilistic framework that addresses the unique hazards and uncertainties of LH_2 bunkering and supports risk-informed decision-making for safe maritime decarbonization.

2. MATERIAL AND METHODS

This section outlines the overall process of the study, which consists of three main methodological stages. First, the general framework of the study is presented, describing the sequential steps adopted in the analysis. Next, the hydrogen port-to-ship bunkering process is explained using the current implementation at the Kobe LH_2 port-to-ship facility as a reference case. Finally, the primary analytical methods employed in this study, FTA, FST, and BN, are described in detail.

2.1. General Framework of the Study

This study consists of three main steps: the risk identification of LH_2 bunkering, the quantification process of the risk, and the BN model analysis to assess the potential risk, as illustrated in Figure 1. The risk identification comprises a literature review process, brainstorming based on expert judgment, and an industry report to generate the FTA and convert it to the BN model. The quantification phase focuses on determining the value of probability based on expert linguistic judgment using Fuzzy set theory (FST). The last step is the analysis of BN, starting with model validation, calculating the variation rate, and sensitivity analysis to assess the most significant risk influencing the failure of LH_2 bunkering.

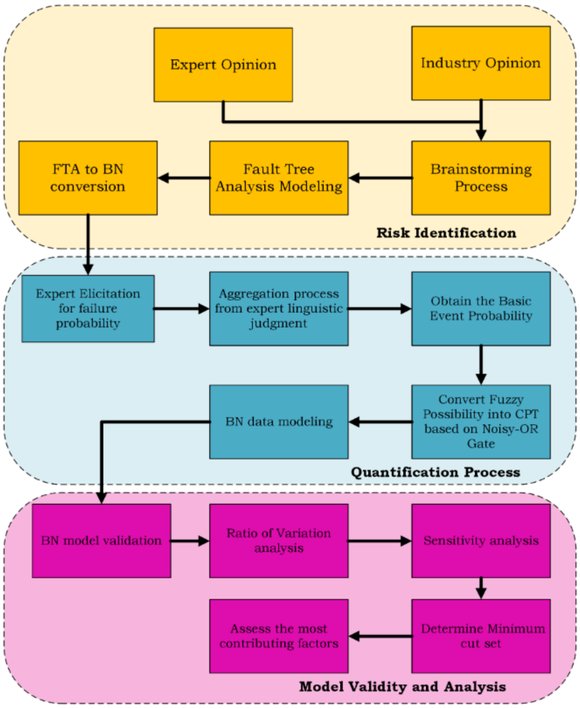


Figure 1. General framework of this study

2.2. Hydrogen Port-to-Ship Bunkering

The transportation of hydrogen by ship is becoming increasingly important as global demand for clean energy rises and the maritime sector pursues decarbonization. It is essential to distinguish between hydrogen bunkering, which refers to supplying hydrogen as fuel for ship propulsion, and hydrogen loading or offloading, which refers to the transfer of hydrogen as cargo for distribution to other markets. This study specifically addresses hydrogen port-to-ship bunkering as a fuel supply operation, rather than hydrogen handling as cargo. Innovative technologies and infrastructure are being developed to enable the safe and efficient transport of hydrogen, including port-to-ship bunkering. This process involves transferring hydrogen, often in liquid form, from storage facilities at ports to ships, which can be complex due to hydrogen's properties and the required infrastructure. The development of hydrogen bunkering facilities is crucial for supporting the maritime industry's decarbonization goals, in line with the IMO commitment to achieving net-zero greenhouse gas emissions by 2050 (Semchukova et al., 2024).

The real-world application of hydrogen port-to-ship bunkering is still limited; the Kobe LH2 port-to-ship facility is the first of its kind globally. As shown in Figure 2, Kobe LH2 has adapted the port-to-ship system for LH2 distribution, with systems for regasifying LH2 and direct delivery by trucks. Researchers may learn from the LNG port-to-ship bunkering process. The port-to-ship bunkering process involves supplying fuel directly from a port facility to a ship, which is one of three common methods for liquid gas bunkering, alongside ship-to-ship and truck-to-ship methods. The port-to-ship method is characterized by its infrastructure requirements and operational efficiency, which are essential for supporting the growing demand for LH2 as a new energy source. However, hydrogen's high flammability requires rigorous safety protocols. Risk assessments, such as those conducted for the Port of Kobe's LH2 terminal, identify critical components and model potential accidents, including fires and explosions, to establish safe separation distances and operational procedures (Schiaroli et al., 2024). Figure 3 shows the detailed components used during the port-to-ship bunkering process, which will be translated into the FTA model.

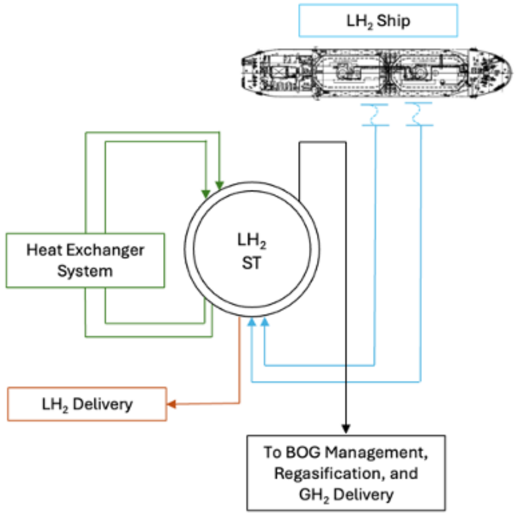


Figure 2. Layout of Kobe LH_2 port-to-ship facility (Schiaroli et al., 2024)), LH_2 ST = LH_2 Storage Tank, BOG = Boil-of-Gas

Safety zones for hydrogen bunkering operations are crucial. Studies have shown that even in worst-case scenarios, such as hose ruptures, the risks can be managed within acceptable limits, ensuring the safety of both the port and surrounding areas (Jeon et al., 2023). Therefore, establishing comprehensive safety measures is vital to mitigate potential hazards associated with hydrogen handling, ensuring that the transition to this cleaner energy source can proceed without compromising public safety or environmental integrity.

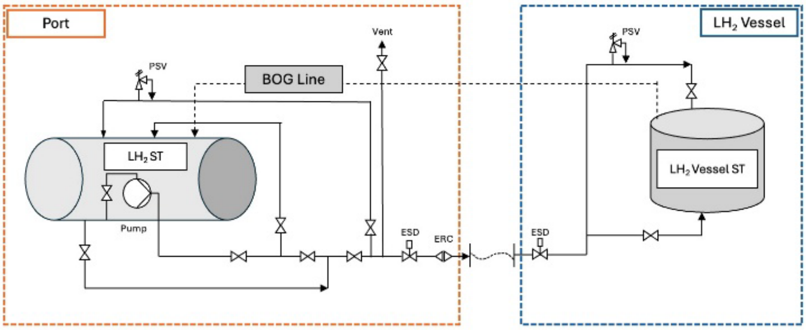


Figure 3. Simplified port-to-ship loading-unloading connection, ESD = Emergency Shut Down, ERC = Emergency Release Coupling, PSV = Pressure Safety Valve

Existing literature highlights hydrogen port-to-ship bunkering compared with alternative fuels such as LNG and ammonia, emphasizing distinct infrastructure and safety challenges. While LNG benefits from a relatively mature bunkering infrastructure and established cryogenic handling practices, hydrogen requires more stringent material specifications and advanced leak prevention measures due to its small molecular size and wide flammability range (Barthélémy, 2012). Although ammonia offers a higher volumetric energy density, its toxicity presents major operational risks, whereas hydrogen's low volumetric energy density necessitates larger storage volumes and more robust containment systems, directly affecting port and ship design (Preuster et al., 2017; Usman, 2022).

Regulatory frameworks and pilot projects are evolving to support hydrogen bunkering adoption. The International Maritime Organization (IMO) and the International Code of Safety for Ships Using Gases or Other Low-Flashpoint Fuels (IGF Code) are expanding their provisions to incorporate hydrogen-specific requirements, while classification societies are developing prescriptive and performance-based rules for bunkering operations (Butt & Markmiller, 2025; Gabov & Lizikova, 2022). Demonstration projects in Kobe, Rotterdam, Antwerp, and Australia are providing empirical evidence on safety protocols and operational feasibility, informing regulatory development and building industry confidence in hydrogen as a marine fuel (Naquash et al., 2023; Visser et al., 2020). These initiatives underscore the importance of integrating empirical data with theoretical assessments to establish globally consistent standards for hydrogen bunkering.

2.3. Fault Tree Analysis

FTA is a top-down, deductive approach to risk analysis that focuses on identifying potential causes of a specific undesirable event, known as the "top event." FTA is a logical, structured method for identifying and evaluating the potential causes of a specific undesirable event (Cem et al., 2019). The process typically involves the following steps:

1. Defining the top event: the undesirable event that is the focus of the analysis.
2. Identifying the immediate causes: the events or conditions that directly contribute to the top event.
3. Identifying the basic events: the lowest-level events or failures that can lead to the immediate causes.

The causal relationships between these events are then represented graphically in a fault tree, using standardized symbols and logic gates (Bobbio et al., 2001). By constructing a fault tree and analyzing the probabilities of the basic events, the overall risk of the top event can be quantified and mitigation strategies developed.

FTA has been widely applied across industries, including the maritime sector, to assess and mitigate risks in complex operations (Akyuz et al., 2020; Kuzu et al., 2019). Its systematic approach to identifying potential causes of undesirable events and quantifying their probabilities makes it particularly valuable for hydrogen bunkering, where the handling and storage of hydrogen introduce unique safety challenges. By applying FTA to hydrogen bunkering operations, ship operators and port authorities can better evaluate risks, design effective mitigation strategies, and enhance the overall safety of hydrogen-powered maritime operations (Atehnjia et al., 2018; Töz et al., 2022).

However, when applied to LH2 bunkering, traditional FTA faces limitations due to a lack of operational data and the inability to capture dependencies and update beliefs as evidence changes. To address these challenges, researchers have integrated FTA with advanced methods such as BN, FST, and dynamic risk assessment frameworks (Aliabadi et al., 2020; Villa et al., 2016). These hybrid approaches improve flexibility by incorporating expert judgement, probabilistic reasoning, and real-time monitoring, enabling both diagnostic and prognostic analysis of risks (Kharchenko et al., 2013; Meel & Seider, 2007). Such advancements make FTA more suitable for hydrogen bunkering operations, providing a robust methodological foundation to assess uncertainties, anticipate cascading failures, and support proactive safety management in the maritime sector (Aliabadi et al., 2024; Birch et al., 2023).

2.4. Fuzzy Set Theory Approach

This section outlines the details of the FST approach employed in this study, which comprises a linguistic term, the equation for the aggregation process, and conversion to a defuzzification value.

2.4.1. Fuzzy Set Theory

The objective of FST is to address the uncertainty between Boolean values (Zadeh, 1965). In this study, fuzzy theory is applied to convert experts' linguistic judgments into numerical probabilities. The experts' linguistic opinions were translated into corresponding fuzzy numbers based on Hsu and Chen (1996). According to Chen and Hwang (1992), there are up to eight scales of fuzzy numbers. However, considering the experts' capabilities and the optimal load on human memory for a particular question, the six-point scale, which includes five choices (Very Low, Low, Medium, High, and Very High), was used (Nicolis & Tsuda, 1985), as shown in Table 1. Fuzzy membership functions, such as triangular and trapezoidal functions, are commonly used to map linguistic terms to numerical values. Although triangular fuzzy numbers are widely used in the maritime and hydrogen industries, this study chose trapezoidal fuzzy numbers, as they provide a better fit for modelling the uncertainty and variability inherent in the data (G. Li et al., 2025). The membership function of fuzzy trapezoidal numbers is explained in the equation below:

$$\mu_{A'}(x) = \begin{cases} 0, x < a_1 \\ \frac{x-a_1}{a_2-a_1}, a_1 \leq x \leq a_2 \\ 1, a_2 \leq x \leq a_3 \\ \frac{x-a_4}{a_3-a_4}, a_3 \leq x \leq a_4 \\ 0, x < a_4 \end{cases} \qquad (1)$$

Linguistic term	Fuzzy numbers
Very low (VL)	(0, 0, 0.1, 0.2)
Low (L)	(0.1, 0.25, 0.25, 0.4)
Medium (M)	(0.3, 0.5, 0.5, 0.7)
High (H)	(0.6, 0.75, 0.75, 0.9)
Very high (VH)	(0.8, 0.9, 1, 1)

Table 1. Linguistic terms and trapezoidal fuzzy numbers of possibilities (W. J. Wang, 1997)

2.4.2. Aggregation Process

There are five steps to convert linguistic judgement into fuzzy numbers based on the Similarity Agreement Method (SAM) developed by Hsu and Chen (1996). Each expert's linguistic value will correspond to a fuzzy membership member of a trapezoidal; for example, $\tilde{A} = (a_1, a_2, a_3, a_4)$ and $\tilde{B} = (b_1, b_2, b_3, b_4)$ based on Lavasani et al. (2015)

2.4.2.1. Determine the degree of similarity

Degree of agreement $S_{uv}(R_u, R_v)$ was estimated between each pair of experts (E_u) and (E_v) with the function of S:

$$S(\tilde{A}, \tilde{B}) = 1 - \frac{1}{4}\sum_{i=1}^{4}|a_i - b_i| \qquad (2)$$

2.4.2.2. Calculation of average agreement

The average agreement was calculated based on the degree of similarity between experts. Therefore, each expert has their own average agreement value according to other experts $AA(E_u)$. The value of M is the number of experts involved.

$$AA(E_u) = \frac{1}{M-1}\sum_{\substack{v=1 \\ u \neq v}}^{M} S(\tilde{R}_u, \tilde{R}_v) \qquad (3)$$

2.4.2.3. Calculation of Relative Agreement (RA) degree

The relative agreement (RA) is calculated to determine the degree of expert compared to the total average agreement of all experts, which can be defined by:

$$RA(E_u) = \frac{AA(E_u)}{\sum_{u=1}^{M} AA(E_u)} \qquad (4)$$

2.4.2.4. Determine the expert weighting

The expert weighting is a normalized score, where each expert's score is divided by the total score of all experts. The $w(E_u)$ can be determined by comparing the value of an expert's professional position, age, experience, education, and subject relevance to all experts. The $w(E_u)$ can be calculated by:

$$w(E_u) = \frac{\sum_{k=1}^{n} S_{ik}}{\sum_{j=1}^{M}\sum_{k=1}^{n} S_{jk}} \qquad (5)$$

Where S_{ik} is the score of experts i for criterion k, n is the number of criteria, and M is the number of experts

2.4.2.5. *Determine the Consensus Coefficient (CC) degree.*

The consensus coefficient (CC) can be determined based on the relative agreement (RA), expert weighting ($w(E_u)$) and Relaxation factors (β). The value of β shows the importance of expert weighting ($w(E_u)$) to the RA. In this calculation, the value of β is 0.5 since the experts are from different backgrounds. The CC can be calculated by equation:

$$CC(E_u) = \beta \cdot w(E_u) + (1-\beta) \cdot RA(E_u) \qquad (6)$$

2.4.2.6. *Calculation of aggregated results from the expert's judgment*

The value of the aggregated results of the expert's judgment ($\tilde{R}_{AG}$) can be calculated by the equation:

$$\tilde{R}_{AG} = CC(E_1) \times \tilde{R}_1 + CC(E_2) \times \tilde{R}_2 + \cdots + CC(E_M) \times \tilde{R}_M \qquad (7)$$

2.4.3. Deffuzification, Fuzzy Possibility and Failure Probability

The defuzzification process should be conducted to quantify the value of fuzzy membership. The method is based on the Centre of Area (CoA) method proposed by Sugeno (1999). The defuzzification equation will vary based on the fuzzy shape. For the trapezoidal fuzzy number $\widetilde{\mathrm{A}} = (\mathrm{a}_1, \mathrm{a}_2, \mathrm{a}_3, \mathrm{a}_4)$ the Defuzzification Possibilities (DFP) value can be obtained by:

$$DFP = \frac{1}{3}\frac{(a_4+a_3)^2 - a_4a_3 - (a_1+a_2)^2 + a_1a_2}{(a_4+a_3-a_1-a_2)} \qquad (8)$$

After the DFP value was obtained, to convert the DFP into failure probability (FP) of equipment, human-related error, and failure within the system, the function proposed by Onisawa (1988) was used. The function is empirically generated by addressing human sensation in logarithmic physical value.

$$FP = \begin{cases} \frac{1}{10^K}, DFP \neq 0 \\ 0, DFP = 0 \end{cases}, K = \left[\left(\frac{1-DFP}{DFP}\right)\right]^{1/3} \times 2.301 \qquad (9)$$

2.5. Bayesian Network

BN is a widely used method for quantifying risk analysis (Hänninen, 2014). By analyzing causal relationships between factors, BN is suitable for investigating safety issues within complex systems, such as the maritime and aviation sectors (Animah, 2024; Waskito et al., 2024; C. Yang & Mott, 2020). The main feature of BN is the concept of conditional probability, which refers to the likelihood of certain conditions occurring due to the influence of causal factors. Conditional probability is essential for the quantitative analysis of BN. The following formula can be used to calculate conditional probability:

$$P(A_i|B_j) = \frac{P(A_i)P(B_j|A_i)}{\sum_{i=1}^{n} P(A_i)P(B_j|A_i)} \qquad (10)$$

where B_j is a child node, A_i is the parent node, $P(A_i|B_j)$ is the posterior probability of A_i when the B_j happen.

Another advantage of BN is that it allows probabilistic updating by modifying the observed probability node in the model (Y. Zhou et al., 2022). Therefore, it can predict the probability of failure in hydrogen bunkering when certain conditions happen (with the modified probability of 100%).

2.5.1. Modelling of BN from FTA

This study aimed to evaluate the safety risks associated with port-to-ship liquefied hydrogen (LH2) bunkering by integrating FTA and FBN. The primary objective was to identify, quantify, and assess potential failure modes that could lead to hazardous incidents during the bunkering process. This research offers a more comprehensive risk assessment framework by utilizing FTA as a structured risk identification tool and integrating it with FBN to incorporate uncertainty.

Applying FTA as a risk identification tool provided a structured and hierarchical approach, enabling the decomposition of major risks into specific contributing factors. However, its ability to fully capture all potential risks in LH2 bunkering requires further examination. The three main intermediate events – hydrogen leakage, human error, and overpressure – represent broad categories encompassing multiple sub-events. While this generalization allows for organized analysis, it may overlook specific failure mechanisms, such as material degradation, valve malfunctions, or emergency response inefficiencies.

Additionally, FTA is a static model and does not inherently account for time-dependent risks such as infrastructure ageing, regulatory changes, or operational variability. As hydrogen bunkering involves complex interdependencies between mechanical systems, human operations, and environmental conditions, a purely FTA-based approach may not fully characterize all possible failure scenarios.

Despite these limitations, integrating FTA with FBN helps mitigate some of these constraints. The probabilistic nature of FBN allows for a more flexible and data-driven risk assessment, accommodating uncertainties and dependencies between various failure events. Therefore, while FTA serves as an effective foundation for identifying major risk factors, its combination with FBN enhances the safety assessment framework's overall accuracy and predictive capability.

The process of converting FTA into BN has been widely proposed by several authors (Sakar et al., 2021; Zhao et al., 2022), particularly in the maritime industry. In contrast to Zhao et al. (2021), who used Boolean Algebra for the conversion to Conditional Probability Tables (CPT) based on the FTA gates, this study introduces a novel adaptation. Instead of directly applying Boolean Algebra, the Defuzzification Possibilities (DFP) value was utilized within the Noisy-OR gate model. The DFP value, which represents a more nuanced approach to handling uncertainty, was integrated into the Noisy-OR gate to better generate the Conditional Probability Tables (CPT). This adaptation enhances the model by incorporating fuzzy logic principles, allowing for a more refined and flexible representation of the probabilities involved, especially when dealing with imprecise or incomplete information. The detailed framework is shown in Figure 4.

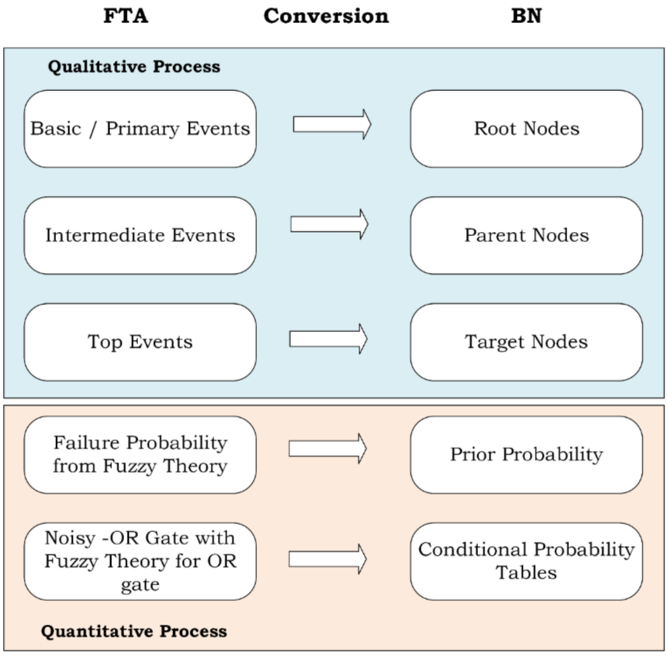


Figure 4. Conversion process from FTA to BN

2.5.2. Noisy-OR gate to Generate CPT

The Noisy-OR Gate model represents the internal relationship between multiple parent nodes and their corresponding child node for the OR Gates in the FTA model (G. Li et al., 2025). The parent and child nodes each have two states (Yes or No), based on the assumption that the network is binary. A child node B has n parents, $A_1, A_2, \dots, A_i, \dots, A_n$. The probability of B under the condition of A_1 can be formulated by

$$P(B \leftarrow A_1) = P(B|A_1, \bar{A}_2, \dots, \bar{A}_i, \dots, \bar{A}_n) \qquad (11)$$

Where $\overline{A_2}$ is the condition when the state of A_2 is on "No" condition. The CPT of B if A_2 occurs can be determined by:

$$1 - P(B \leftarrow A) = \prod_{A_i \in A}(1 - P(B \leftarrow A_1)) \qquad (12)$$

The value of $P(B \leftarrow A_1)$ can be obtained from the value of DFP from expert elicitation.

The Noisy-OR Gate was used for a specific reason. According to the literature, if the gate is OR, the conditional probability table (CPT) will be binary; however, this does not reflect the natural cause, as there is a possibility that the intermediate event (IE) will not occur even if all basic events happen (Zhao et al., 2022), particularly in high-safety contexts such as the maritime sector. Therefore, to improve the model's reliability, the CPT was generated using expert judgement rather than Boolean values (Qiao et al., 2020b).

Additionally, in this case, there is a small possibility that the IE or top event (TE) can occur when the relevant basic events are inactive, due to real-world uncertainty. Consequently, a LEAK value of 0.01 was used in the CPT for this condition. The assumption for this small baseline is to account for incomplete knowledge, data limitations, or unmodelled events (Waskito et al., 2025). By assigning a leak probability of 0.01, the model avoids the unrealistic assumption that the TE is impossible when all basic events are inactive, which is the assumption for the OR-Gate with Boolean values. Similar practice has been reported in several studies employing fault tree analysis (FTA) to Bayesian networks (BN), where a designated leak value has been used to ensure that the CPT remains robust (X. Li et al., 2025; Z. Wang et al., 2025).

2.5.3. Sensitivity Analysis

In the context of BN, sensitivity analysis was conducted to examine causal relationships between nodes and validate the model. The objective was to identify the nodes that exert the most significant influence on the target nodes (Jiang et al., 2020). In this analysis, the sensitivity analysis method used the sensitivity tornado embedded in the GENIE software. The target node must be selected before the sensitivity analysis, and the output is the sensitivity tornado chart and the color of the nodes. The red color means the node has the most significant impact on the targeted node.

2.5.4. Rate of Variation

This study presents the fuzzy ratio of variation (RoV), quantifying the relationship between prior and posterior probabilities to identify the primary events (human factors) that contribute most significantly to the accident scenario. The fuzzy RoV for each primary event is determined using the equation below (Zarei, 2019):

$$RoV\ (A_i) = \frac{\pi(A_i) - \theta(A_i)}{\theta(A_i)} \qquad (13)$$

where $\pi(A_i)$ is the posterior probability while $\theta(A_i)$ is the prior probability of A_i after the analysis of the BN.

3. RESULTS

This section presents the main results of the safety analysis for the port-to-ship LH_2 bunkering process. First, the FTA model is developed to identify critical BE and IE to bunkering failure. The subsequent subsection quantifies the probability using FST based on expert linguistic judgment. The obtained values are then integrated into the BN model derived from the FTA structure. The posterior probabilities from the BN are evaluated to determine the likelihood of the TE under different scenarios. Model validation is conducted to ensure consistency and logical propagation within the network. Finally, the RoV, sensitivity analysis, and minimum cut set identification are performed to determine the most influential causal factors and critical failures in LH_2 bunkering operations.

3.1. FTA Modelling

Figure 5 presents the detailed FTA model for hydrogen bunkering failure. In total, there are 25 BE and 13 IE that comprise this FTA model. The details of the BEs in this study are provided in Table 5, while the IEs are listed in Appendix A. The FTA model was generated based on several studies, including Borgheipour et al. (2021) for hydrogen tank leakage, Zhang et al. (2024) for hydrogen station leakage, Aliabadi et al. (2020) for leakage from hydrogen gasholders, Bulat et al. (2024) for the influence of human factors in hydrogen storage, and EMSA (2022), which conducted a risk analysis of hydrogen-fueled ships.

There are three main intermediate events: Hydrogen Leakage (IE10), Human Error (IE11), and Overpressure (IE12), as shown in Figure 5. Hydrogen leakage is one of the most frequent failures in the bunkering process and should therefore be included as an intermediate event. Human error is categorized as an intermediate event because it can directly affect bunkering performance, rather than being included in specific intermediate or basic events. There are four basic events related to human error, represented by the preconditions of unsafe acts (BE11, BE13, and BE14) and unsafe acts (BE12), according to the Human Factors and Classification Systems (HFACS) (Shappell & Wiegmann, 2003). Pressure failure is classified as an intermediate event because a key factor in the bunkering process is maintaining pressure between the port tank, hose, and receiving tank to ensure sufficient flow during hydrogen transfer.

In the proposed FTA model for hydrogen bunkering failure, most gates linking BEs to IEs are represented as OR-gates. However, certain pressure-related failures, such as mechanical failure, purging gas failure, and thermal expansion, are modelled using AND-gates, as the occurrence of a single BE is insufficient to initiate the corresponding IE. For example, IE6 (Mechanical Failure) requires the simultaneous occurrence of four BEs. A single event, such as BE18 (Power Interruption), cannot independently trigger IE6 without the concurrent occurrence of the remaining BEs.

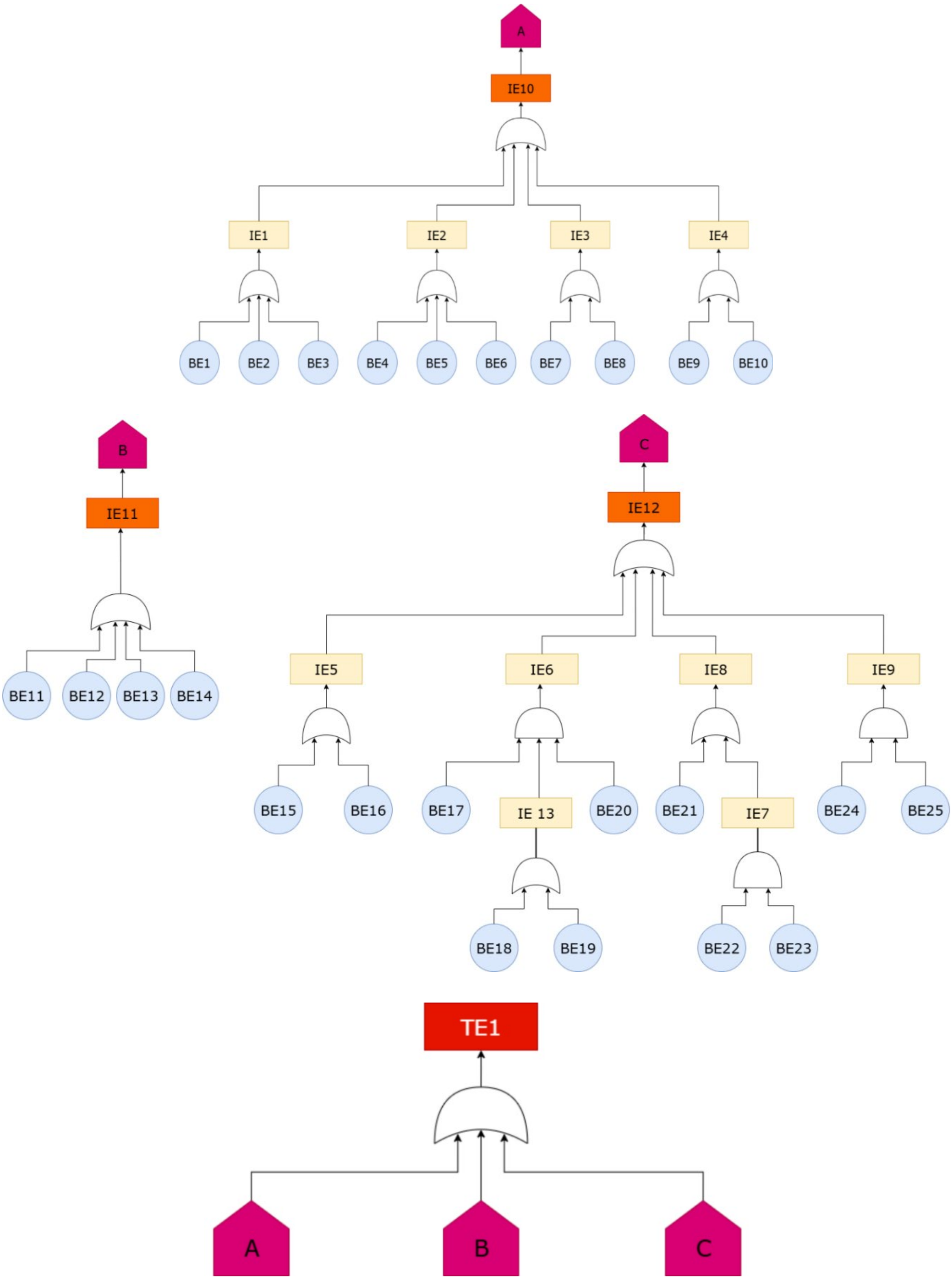


Figure 5. The Fault Tree of failure of LH2 bunkering from port-to-ship

3.2. Calculation of Basic Event Probability by Fuzzy Set Theory

3.2.1. Experts data

In this study, five experts were selected to provide judgments for the modelling of FTA and to offer expert linguistic expertise for hydrogen bunkering safety. The selection deliberately included individuals from diverse backgrounds to ensure that various dimensions of knowledge were represented and that the limitations of each perspective could be complemented by others. Two experts were hydrogen researchers, contributing in-depth technical understanding of hydrogen properties and associated risks, although they had limited direct maritime operational experience. One expert represented maritime safety academia, contributing theoretical knowledge, methodological rigor, and an understanding of regulatory and safety frameworks. Additionally, two experts from the LNG industry were included, providing practical insights from established bunkering operations relevant to hydrogen due to the similarity of handling processes. This varied composition was chosen to balance research-based insights with operational experience, thereby enhancing the robustness, credibility, and applicability of the expert judgments used in the model. Table 2 presents the expert scores based on the specified indicators, offering a detailed assessment of each factor according to the expert evaluations, which are based on relevant studies in the maritime sector (Bulat et al., 2024; Qiao et al., 2020b, 2020a). There is one novel indicator that is rarely used in scoring experts: subject relevance. It is essential to score the experts based on their relevance to the subject, particularly in this study involving several experts from hydrogen technology, academia, and the LNG industry.

Indicator	Classification	Score
Professional Position	Principal academic, researcher, or Ship’s Captain, CEO	5
	Senior academic, 1st Officer, or Chief Engineer, Manager	4
	Junior Academic, 2nd - 3rd Officer, Marine Superintendent	3
	Engineer	2
	Technician	1
Experience	>30 years	5
	20 to 30 years	4
	10 to 20 years	3
	6 to 9 years	2
	1 to 5 years	1
Education Level	Ph.D	5
	Master	4
	BS.E	3
	Junior college	2
	School Level	1
Subject Relevancy	Expert or working in Hydrogen facilities or hydrogen ships (maritime)	5
	Working or Research on Hydrogen	4
	Experienced in maritime activities as officers (non-hydrogen)	3
	Researcher in the maritime sector	2
	Engineering in General	1
Age	>50	5
	40 to 49	4
	30 to 39	3
	25 to 29	2
	<25	1

Table 2. Expert score based on the indicator

Table 3 displays the expert weighting based on their individual scores, reflecting the relative importance assigned by each expert to the various indicators. This table highlights how each expert’s assessment contributes to the overall evaluation, with the weights calculated to ensure that the experts' perspectives are appropriately represented in the final analysis.

Expert	Professional Position	Experience	Education Level	Subject Relevancy	Age	Expert Weighting (*w(Ei)*)
Expert 1 (Hydrogen Researcher)	5	3	5	4	5	0.231
Expert 2 (Principal Academic in Maritime)	5	4	5	2	4	0.210
Expert 3 (LNG Industry)	3	3	4	3	3	0.168
Expert 4 (Hydrogen Researcher)	4	2	5	4	4	0.2
Expert 5 (LNG Industry)	4	4	3	3	4	0.189

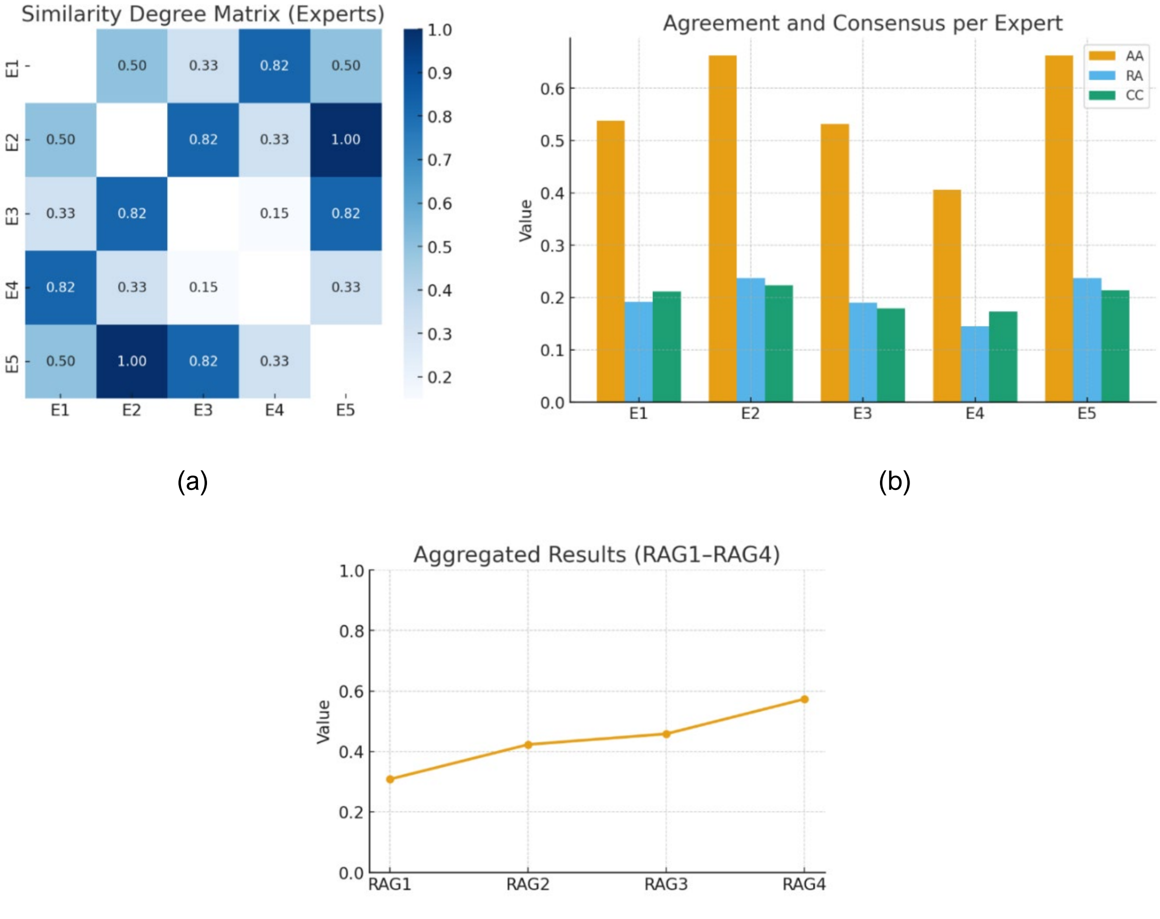
Table 3. Expert weighting based on their individual score

3.2.2. Results of expert elicitation

Table 4 presents the detailed values of the expert linguistic assessments, while the results of the fuzzy agreement analysis are shown in Figure 6. The similarity degree matrix (Figure 6a) highlights the pairwise alignment between experts. The strongest agreement was observed between Expert 2 and Expert 5 (S = 1.0), while the weakest was between Expert 3 and Expert 4 (S = 0.15), indicating variability in expert judgments. Figure 6b illustrates the distribution of average agreement degree (AA), relative agreement degree (RA), and consensus coefficient (CC) across the five experts. Experts 2 and 5 achieved the highest values across all indices, suggesting stronger consistency and influence in shaping the overall consensus, whereas Expert 4 exhibited the lowest values, reflecting a more divergent perspective. The aggregated results (Figure 6c) show a clear increasing trend from RAG1 (0.309) to RAG4 (0.574), confirming the progressive convergence of expert opinions during the fuzzy aggregation process. From these aggregated values, the defuzzification possibility was determined as FP = 0.441, which was subsequently used to calculate the failure probability of the basic event BE2, yielding P(BE2) = 0.003236. These outcomes demonstrate the robustness of the fuzzy consensus framework in quantifying expert judgment and translating it into probabilistic safety assessment.

Expert	Linguistic Term	Fuzzy Number
Expert 1	High (H)	(0.6, 0.75, 0.75,0.9)
Expert 2	Low (L)	(0.1,0.25,0.25,0.4)
Expert 3	Very Low (VL)	(0,0,0.1,0.2)
Expert 4	Very High (VH)	(0.8,0.9,1,1)
Expert 5	Low (L)	(0.1,0.25,0.25,0.4)

Table 4. The expert linguistics for BE2 and its fuzzy membership degree



(a)

(b)

(c)

Figure 6. (a) Similarity degree matrix between experts (E1–E5). (b) Average agreement degree (AA), relative agreement degree (RA), and consensus coefficient (CC) per expert. (c) Aggregated results (RAG1–RAG4) showing convergence of expert opinions.

Table 5 summarizes the expert elicitation results for 25 basic events (BEs) associated with port-to-ship liquefied hydrogen bunkering. Expert judgments were expressed using linguistic variables (e.g., Very Low, Low, Medium, High, Very High), which were then transformed into fuzzy numbers. Through aggregation and defuzzification, these qualitative assessments were transformed into quantitative possibility values (DFP) that can be directly used in probabilistic safety modeling frameworks such as FTA and BN.

The results show that human-related factors are among the most critical contributors. For example, BE14 (Human-Machine Interface Problem) has the highest defuzzified probability (0.651), followed by BE11 (Inadequate Personnel Skills) and BE12 (Task Execution Problem), both at 0.614. These findings emphasize the significant impact of human reliability on hydrogen bunkering safety. In contrast, technical issues such as BE25 (Improper Insulation, DFP = 0.292) and BE20 (Pressure Relief Valve Failure, DFP = 0.300) are considered less probable, though still relevant within the overall fault tree structure. This distribution of values highlights the importance of addressing both technical and human factors to ensure a comprehensive risk assessment.

Identifier	Basic Events	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Aggregated Fuzzy Number				DFP
BE1	Hose Rupture (Material Degradation)	L	L	L	L	L	0.100	0.250	0.250	0.400	0.250
BE2	Hose Design Error	H	L	VL	VH	L	0.309	0.423	0.458	0.574	0.441
BE3	Hose Vibration	L	L	L	L	H	0.179	0.329	0.329	0.479	0.329
BE4	Valve Fatigue and Strength Loss	L	VL	L	L	L	0.081	0.202	0.221	0.361	0.217
BE5	Valve Corrosion	M	L	L	M	H	0.276	0.447	0.447	0.619	0.447
BE6	Improper Valve Connection	H	VL	M	L	H	0.328	0.460	0.479	0.629	0.475
BE7	Strong Wind	M	VL	M	M	M	0.248	0.413	0.430	0.613	0.427
BE8	High Waves	M	VL	H	M	M	0.299	0.455	0.473	0.647	0.470
BE9	Improper Loading	M	L	M	L	H	0.272	0.443	0.443	0.614	0.443
BE10	Collision/contact	H	VL	L	M	L	0.217	0.347	0.367	0.517	0.364
BE11	Inadequate Personnel Skills	H	L	M	H	H	0.455	0.614	0.614	0.773	0.614
BE12	Task Execution Problem	H	L	M	H	H	0.455	0.614	0.614	0.773	0.614
BE13	Fatigue	H	M	L	M	H	0.390	0.561	0.561	0.732	0.561
BE14	Human-Machine Interface Problem	H	M	H	M	H	0.481	0.651	0.651	0.821	0.651
BE15	Regulator Setting Failure	H	L	M	L	L	0.232	0.391	0.391	0.551	0.391
BE16	Pressure Regulator Malfunction	H	L	L	L	L	0.189	0.339	0.339	0.489	0.339
BE17	Emergency Safety Devices Failure	M	L	L	L	M	0.180	0.350	0.350	0.521	0.350
BE18	Power Interruptions	M	L	M	L	M	0.221	0.401	0.401	0.581	0.401
BE19	Pump Malfunctions	M	L	L	L	M	0.180	0.350	0.350	0.521	0.350
BE20	Pressure Relief Valve Failure	M	L	L	L	L	0.140	0.300	0.300	0.460	0.300
BE21	Purging Procedure Failure	H	L	M	L	L	0.232	0.391	0.391	0.551	0.391
BE22	Inadequate Volume and Flow Rate	M	L	M	L	L	0.178	0.348	0.348	0.517	0.348
BE23	Inappropriate Purging Gas	M	L	M	L	L	0.178	0.348	0.348	0.517	0.348
BE24	Sudden Hydrogen Temperature Increase	M	L	M	L	L	0.178	0.348	0.348	0.517	0.348
BE25	Improper Insulation	L	L	M	L	L	0.134	0.292	0.292	0.450	0.292

Table 5. Experts' linguistic value and Defuzzification possibilities for each basic event

3.3. BN Modelling from FTA

3.3.1. CPT from Fuzzy set

Table 6 shows the DFP value of BE1, BE2, and BE3 to IE1. The aggregation process was similar for converting the fuzzy linguistic value for the basic event, except for converting DFP to the Failure probability. The value of CPT as an input in BN was based on the DFP and equations 11 and 12. For example, the calculation value of basic events (BE1, BE2, and BE3) to IE1 will be explained below, and the detailed CPT is stated in Table 7.

Aggregation from expert judgment on the previous table

$$P(IE1 \leftarrow BE1) = 0.5013 \qquad P(IE1 \leftarrow BE2) = 0.640 \qquad P(IE1 \leftarrow BE3) = 0.5026$$

Conditional Probability calculation Noisy-OR model

$$P(IE1 \leftarrow BE1, BE2) = 1 - \big(1 - P(IE1 \leftarrow BE1)\big) * \big(1 - P(IE1 \leftarrow BE2)\big) = 0.8204$$

$$P(IE_1 \leftarrow BE1, BE3) = 1 - \big(1 - P(IE1 \leftarrow BE1)\big) * \big(1 - P(IE1 \leftarrow BE3)\big) = 0.7520$$

$$P(IE1 \leftarrow BE2, BE3) = 1 - \big(1 - P(IE1 \leftarrow BE2)\big) * \big(1 - P(IE1 \leftarrow BE2)\big) = 0.8209$$

Basic or Intermediate Event	Intermediate Event	Description of Intermediate Event	Ex 1	Ex 2	Ex 3	Ex 4	Ex 5	DFP = P(IE=Yes|BE=Yes)
BE1	IE1	Hose Failure	M	L	L	H	H	0.501
BE2			H	VH	L	VH	L	0.640
BE3			M	M	L	M	H	0.503

Table 6. The DFP number from the BE1, BE2, and BE3 to IE1

Table 7 presents the Conditional Probability Table (CPT) for IE1 (the initiating event) and Basic Events 1 (BE1), 2 (BE2), and 3 (BE3). CPT shows the conditional probabilities that describe the likelihood of various outcomes based on the occurrence or non-occurrence of these basic events. Specifically, it outlines how the probability of IE1, the initiating event, is influenced by the presence or absence of BE1, BE2, and BE3. The values in the CPT are derived from expert judgments and previous calculations, reflecting the interdependencies between the initiating event and the basic events.

Basic Events	Conditional Cases							
BE1	Yes				No			
BE2	Yes		No		Yes		No	
BE3	Yes	No	Yes	No	Yes	No	Yes	No
P(IE1=Yes)	0.9107	0.8204	0.7519	0.5013	0.8209	0.6400	0.5026	0.01
P(IE1=No)	0.0892	0.1795	0.2480	0.4986	0.1790	0.3599	0.4973	0.99

Table 7. The Conditional Probability Table (CPT) for IE 1 and BE1, BE2, and BE3

3.4. Evaluation of Posterior Probability

Figure 7 presents the posterior probability values derived from the FTA-BN model for LH_2 bunkering operations from port to ship. The probability of the top event, TE1 (Bunkering Failure), is 8.08%, indicating that under normal operating conditions with the given prior probabilities, the likelihood of bunkering failure is 0.0808. Among the intermediate events (IEs), the highest posterior probability corresponds to IE11 (Human Error) at 3.76%, followed by IE10 at 3.68%. This highlights the dominant contribution of human-related errors in the bunkering process. Conversely, several IEs (IE6, IE7, and IE9) exhibit posterior probabilities of only 1%. This outcome arises from their representation through an AND-gate in the fault tree, combined with a LEAK probability of 0.01. In such configurations, the occurrence of a single basic event failure is insufficient to trigger the intermediate event, thereby limiting its probability to 0.01. At the basic event (BE) level, the highest prior probability is associated with BE14

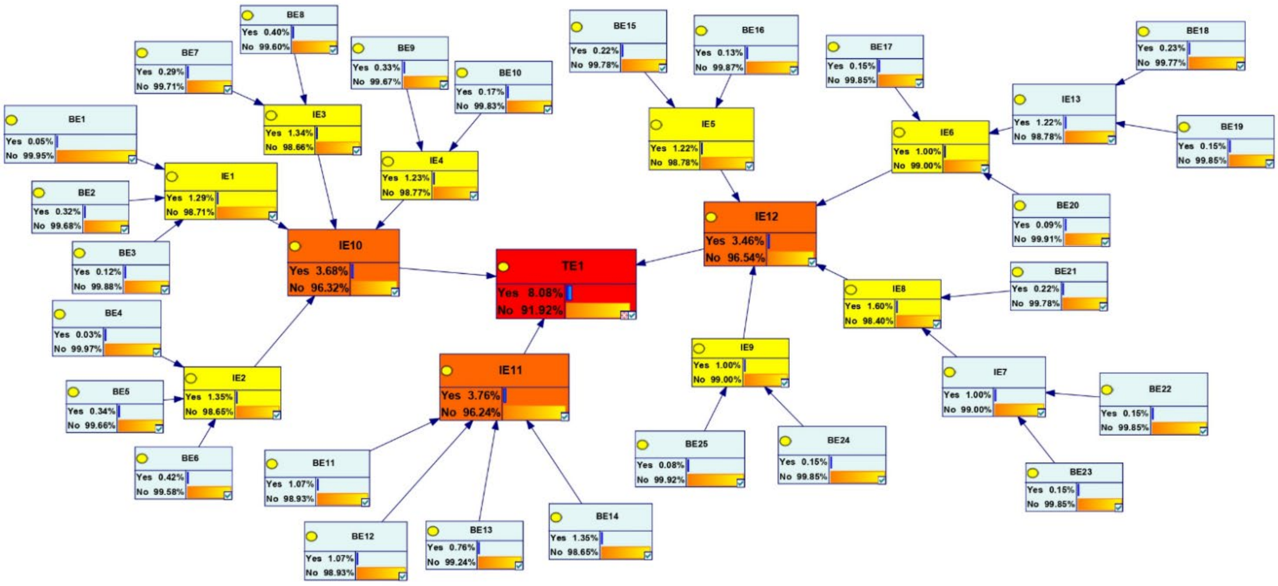


Figure 7. The posterior probability results from converting FTA to BN

3.5. Model Validation

Validation is a critical step in BN modeling to ensure the model's reliability and consistency with the causal mechanisms underlying maritime operations. The model should accurately reflect the logical propagation of probabilities across different event levels. For example, in real maritime operations, an increase in the probability of a BE is expected to result in a corresponding increase in the probability of the associated IE, and ultimately the TE. This behavior confirms that the model preserves the causal structure of the system. Furthermore, validation provides confidence that the BN not only represents mathematical correlations but also captures meaningful cause-and-effect relationships that align with expert knowledge and operational experience. By performing such validation, the model can be considered credible and applicable for safety analysis in maritime contexts.

In the maritime sector and BN modeling, the three-method axiom is one of the most applicable methods due to its robustness and suitability for systems lacking real accident data (P. Li et al., 2024; Pristrom et al., 2016). The first axiom requires that an increasing number of parent nodes should also be reflected in the corresponding child node. For the second axiom, the proliferation of the posterior probability of the child node should be consistent from the least probable to the most probable failure (100%). Figure 8 shows the variation of the TE1 value based on different probabilities of its IE. The value of TE1 increases with higher values of its child nodes (IE10, IE11, IE12). Moreover, according to the graph, there are no fluctuations in the chart. Consequently, the model satisfies the requirements for Axioms 1 and 2.

For axiom 3, the requirement is that the summative effect of the parent nodes should be greater than the individual effect of each parent node on the child node. Table 8 shows that when the evidence (100%) value was entered for IE1, IE2, IE3, and IE4 individually, the posterior probability of IE10 is 65.67%, 57.46%, 46.03%, and 46.44%, respectively. When the evidence for those IEs is entered simultaneously, the posterior probability of IE10 increases to 95.41%, satisfying axiom 3. Table 8 also shows a similar scenario for child node IE11 and its parent nodes. The same process was performed for every child node in the FTA-BN model, and the results meet the requirement for axiom 3.

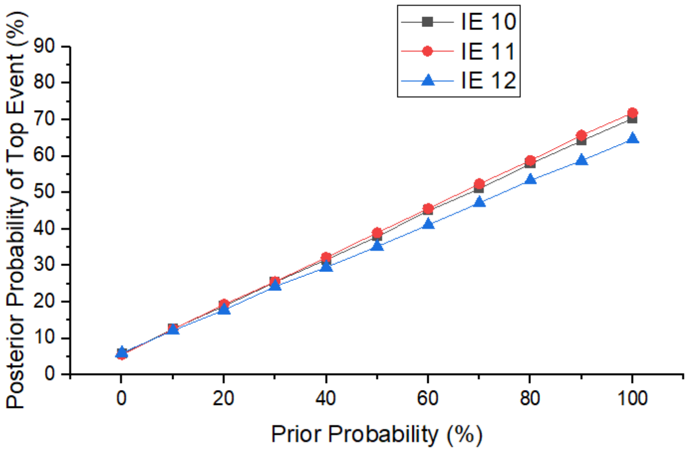


Figure 8. Axiom test for the BN model

Child Nodes	Parent Nodes Occurred (100% Probability)	Posterior Probability of Child node (TE1) (%)	Child Nodes	Parent Nodes Occurred (100% Probability)	Posterior Probability of Child node (TE1) (%)
IE10 (Hydrogen Bunkering Failure)	IE1	65.67	IE11 (Human Error)	BE11	67.31
	IE2	57.46		BE12	70.52
	IE3	46.03		BE13	62.93
	IE4	46.44		B14	67.51
	All parent nodes	95.41		All parent nodes	98.74

Table 8. Axiom 3 test results for IE10 and IE11

3.6. Rate of Variation (RoV) and Ranking

RoV analysis aims to determine which BE has the most significant difference after the BN analysis. The analysis was conducted by applying the top-event (TE1) probability to the worst-case value, 100% probability. Thus, the value of posterior probability can be obtained. Table 9 shows that BE14 and BE12 have the highest values, with 8.42E-02 and 6.92E-02, while BE1 and BE4 have the lowest posterior probability, with 5.93E-4 and 3.30E-04.

Identifier	Basic Events	Prior Probability	Posterior Probability
BE1	Hose Rupture (Material Degradation)	4.80E-04	1.66E-03
BE2	Hose Design Error	3.24E-03	1.34E-02
BE3	Hose Vibration	1.20E-03	4.17E-03
BE4	Valve Fatigue and Strength Loss	2.98E-04	7.88E-04
BE5	Valve Corrosion	3.39E-03	9.82E-03
BE6	Improper Valve Connection	4.19E-03	1.26E-02
BE7	Strong Wind	2.90E-03	7.49E-03
BE8	High Waves	4.02E-03	1.12E-02
BE9	Improper Loading	3.29E-03	8.34E-03
BE10	Collision/contact	1.69E-03	4.60E-03
BE11	Inadequate Personnel Skills	1.07E-02	6.64E-02
BE12	Task Execution Problem	1.07E-02	6.92E-02
BE13	Fatigue	7.57E-03	4.43E-02
BE14	Human-Machine Interface Problem	1.35E-02	8.42E-02
BE15	Regulator Setting Failure	2.16E-03	7.31E-03
BE16	Pressure Regulator Malfunction	1.34E-03	4.53E-03
BE17	Emergency Safety Devices Failure	1.49E-03	1.49E-03
BE18	Power Interruptions	2.34E-03	2.34E-03
BE19	Pump Malfunctions	1.49E-03	1.49E-03
BE20	Pressure Relief Valve Failure	8.85E-04	8.85E-04
BE21	Purging Procedure Failure	2.16E-03	5.89E-03
BE22	Inadequate Volume and Flow Rate	1.45E-03	1.45E-03
BE23	Inappropriate Purging Gas	1.45E-03	1.45E-03
BE24	Sudden Hydrogen Temperature Increase	1.45E-03	1.46E-03
BE25	Improper Insulation	8.09E-04	8.11E-04

Table 9. Posterior Probability of the basic event after the probability of the top event is set to failure

Figure 9 presents the results of the RoV calculation based on equation 13. BE12 (Task Execution Problem) has the highest RoV value at 5.48, followed by BE11 (Inadequate Personnel Skills) with a value of 5.22. Figure 9 also shows that the basic events related to human error (BE11–BE14) have the highest RoV values compared to other BEs. This indicates that failures involving humans can significantly increase the probability of TE1 occurring. As a result, these findings suggest the need to improve human capabilities, such as through training and human-centered design, to reduce the significant impact of human factors on accidents.

In contrast, several basic events do not directly contribute to the RoV of TE1. These events are linked to their respective intermediate events through AND-gates, meaning that their individual failure alone is not sufficient to cause hydrogen bunkering failure. Instead, they must occur together with other contributing basic events to affect the top event.

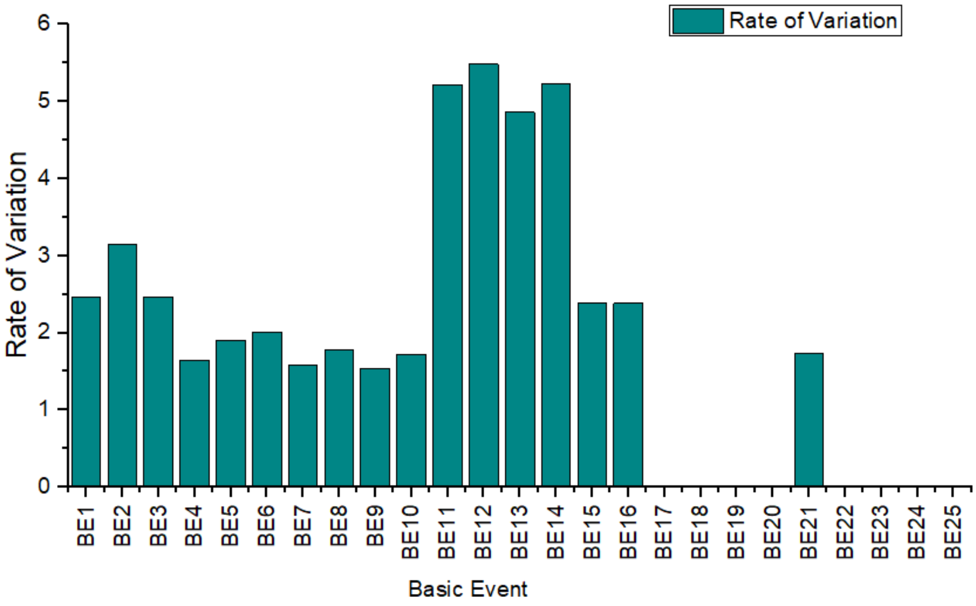
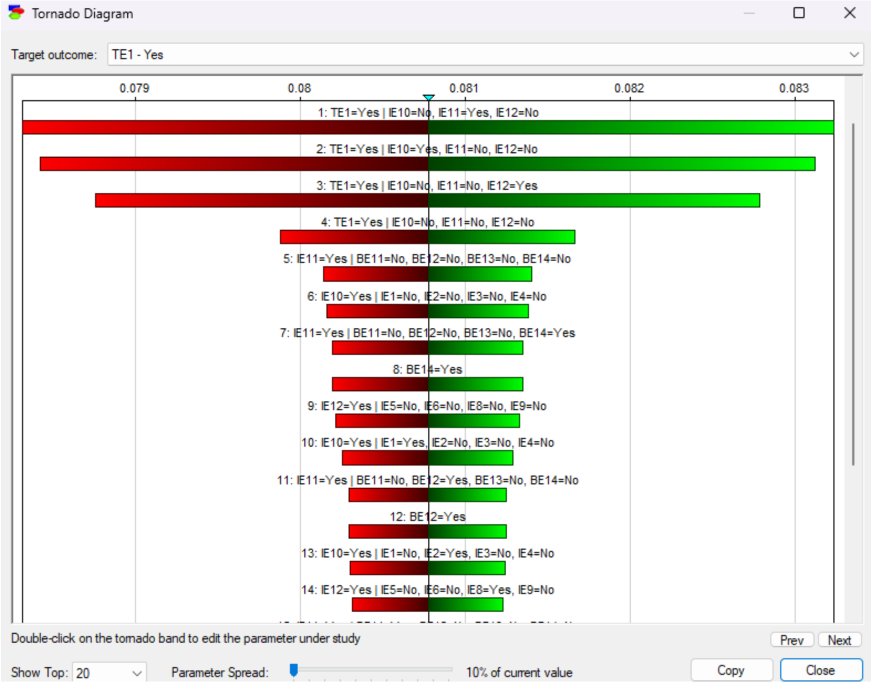


Figure 9. The Rate of Variation (RoV) of each basic event

3.7. Sensitivity Analysis

The sensitivity analysis was conducted using the NETICA sensitivity tornado, with the target node set as the Top event of hydrogen bunkering failure. According to Figure 10, the current probability of TE1 is 0.0808, with a reachable range between 0.0783 and 0.0832 when the parent nodes are varied within 10% of their current values. The bars in Figure 10 indicate how the probability of the Top event (TE1 = Yes) changes when the probability of a given parent node is adjusted within the specified range. Longer bars indicate a stronger influence on the target nodes. Among the contributing factors, the most influential IEs are IE10, IE11, and IE12, as shown by their dominant position in the tornado diagram. In terms of BE, the most significant basic event contributing to the inability of LH2 bunkering is BE14, followed by BE12, along with other human-related error events. These findings corroborate the results from RoV analysis, which show that human errors are the primary determinants of bunkering safety risk. The sensitivity analysis also supports these results, as indicated by the color of the node in Figure 11. The red node, BE11-BE14, has a more significant impact on the target node, TE1. The tornado diagram thus provides strong evidence that the BN model preserves the expected causal structure, validating its application for safety assessment in LH_2 bunkering operations.



Target outcome: TE1 - Yes

1: TE1=Yes | IE10=No, IE11=Yes, IE12=No
2: TE1=Yes | IE10=Yes, IE11=No, IE12=No
3: TE1=Yes | IE10=No, IE11=No, IE12=Yes
4: TE1=Yes | IE10=No, IE11=No, IE12=No
5: IE11=Yes | BE11=No, BE12=No, BE13=No, BE14=No
6: IE10=Yes | IE1=No, IE2=No, IE3=No, IE4=No
7: IE11=Yes | BE11=No, BE12=No, BE13=No, BE14=Yes
8: BE14=Yes
9: IE12=Yes | IE5=No, IE6=No, IE8=No, IE9=No
10: IE10=Yes | IE1=Yes, IE2=No, IE3=No, IE4=No
11: IE11=Yes | BE11=No, BE12=Yes, BE13=No, BE14=No
12: BE12=Yes
13: IE10=Yes | IE1=No, IE2=Yes, IE3=No, IE4=No
14: IE12=Yes | IE5=No, IE6=No, IE8=Yes, IE9=No

Double-click on the tornado band to edit the parameter under study

Show Top: 20
Parameter Spread: 10% of current value

Figure 10. The result of sensitivity tornado with Top Event failure as the target

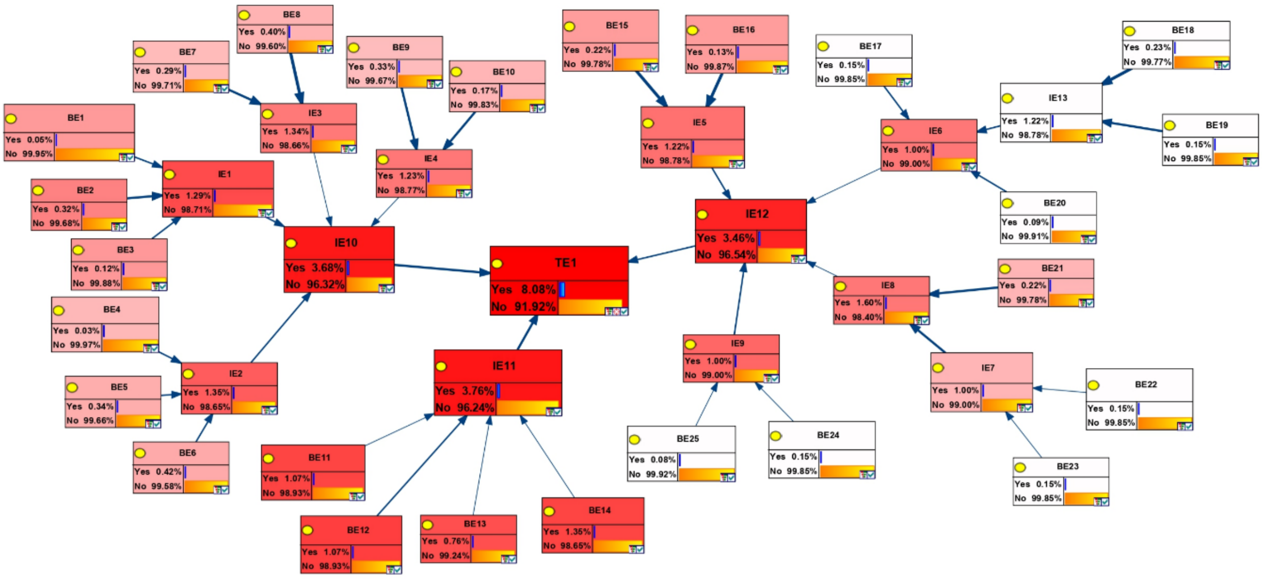


Figure 11. The sensitivity analysis by colour and line influences from BE to TE$_{Minimum\ Cut\ Sets}$

Selecting the minimum cut set determines which single basic event will cause failure (Zhao et al., 2022). The influence is indicated by the thickness of the line, as shown in Figure 11. Thicker lines represent a greater influence on the intermediate and top event nodes (Zhao et al., 2021). The minimum cut set is selected from three intermediate events. For IE10 (Hydrogen Leakage), the minimum cut set is the Basic Event BE2 (Hose Degradation Error); for IE11 (Human Error), it is BE12 (Task execution problem); and for IE12 (Pressure Failure), it is Regulator Setting Failure (BE15), as shown in Table 10.

Intermediate Event	Minimum cut sets
Hydrogen Leakage	BE2→IE1→IE10→TE1
Human Error	BE12→IE11→TE1
Pressure Failure	BE15→IE5→E12→TE1

Table 10. The minimum cut set based on its intermediate event

4. DISCUSSION

The conversion of FTA to a BN was performed to clarify the interdependence among failure events within the FTA. BN further enhances FTA by enabling probabilistic inference, allowing prediction of how changes in the likelihood of basic events affect the top event, thus addressing FTA's limitations. Additionally, sensitivity analysis within BN can be used to identify the minimum cut sets of the FTA, strengthening the risk assessment process.

The findings successfully addressed the research question regarding critical risks in LH2 bunkering. The FTA model identified three key intermediate events: hydrogen leakage, human error, and overpressure, which were further analyzed through expert judgment and FST to quantify their likelihood and impact. the model was also validated using sensitivity analysis, ensuring that the most influential risk factors were adequately captured. Therefore, the study fulfilled its purpose by systematically assessing safety risks and highlighting the most critical failure modes in LH2 bunkering operations.

In this study, failure probabilities were derived from expert judgment rather than equipment failure data, as available data primarily pertained to other fuels, such as LNG and methanol, which have different properties from LH2. By incorporating insights from five experts with diverse backgrounds, including researchers in the hydrogen industry, maritime safety researchers, and experts in the LNG industry, the accuracy and reliability of probability estimations were improved, leading to a more informed risk assessment. However, this diversity results in significant differences between experts' linguistic judgments, as seen in the assessments of Experts 3 and 4 for the failure probability of BE2 (Hose Design Error). Expert 3, from the LNG industry, believes the probability of a design error leading to hose failure is very low. In contrast, Expert 4, a hydrogen researcher with minimal real-world maritime experience, considers the design error likely to cause hose failure. These differences stem from each expert's background and practical exposure to specific contexts. Importantly, both perspectives are valid, reflecting complementary dimensions of knowledge: one grounded in established operational practice and the other in precautionary, research-based risk perception.

The findings of this study are consistent with relevant research that used FTA-Fuzzy BN for hydrogen storage, bunkering, and refueling stations. Human factors emerge as the most critical contributors to top-event failures, consistent with previous studies such as Wang and Gao (2023) and Zhang et al. (2024), which highlight issues like inadequate skills and task complexity. However, compared to similar studies on maritime LH2 bunkering, notable differences appear in the highest RoV of basic events. Studies by Tamburini et al. (2025, 2024) reported that equipment failures, such as pressure shock in the hose, ESD sensor, and ignition source failures, influence the most basic events. These discrepancies are due to differences in study objectives. Tamburini et al. (2024) focused on determining the performance of safety barriers, while Tamburini et al. (2025) examined safety resilience. Moreover, these studies do not integrate human factors into the FTA and FBN.

Human-related errors are the primary contributors to failures in LH2 bunkering, exhibiting the highest prior probability and sensitivity according to BN analysis. The most influential basic event is BE 12 (Task Execution Problem), mainly due to the novelty of hydrogen technology, which seafarers have not previously operated. When confronted with unfamiliar challenges, such as hydrogen systems and automation, seafarers experience increased cognitive load, particularly in updating their mental models, processing information, and translating it into effective action planning (Sezer et al., 2024), which is informed by human experience and knowledge integrated into the system (France, 2017). As the hydrogen bunkering system is considered new, there is a high likelihood that seafarers will face significant difficulties when executing tasks. Therefore, adequate training and simulation are necessary before seafarers perform these tasks.

This study considers the probability and significance of components contributing to bunkering failure, such as hose, valve, and ESD, as non-influential factors. This is because these components and equipment are specifically designed for hydrogen transport. Moreover, the low involvement of component failures, especially regarding ESD, pump malfunctions, and pressure relief valves, is due to the AND-Gate logic, which requires all contributing factors to be present for the intermediate event to occur. This concept limits the effect of basic events related to components on the TE. Consequently, material failure is considered minimal with proper manufacturing, maintenance, and operation, supported by thorough design and testing processes.

The results of this study were also compared with similar studies on risk analysis of LNG bunkering using FTA and FBN. Human error is identified as the most significant failure during bunkering operations by Vairo et al. (2021), specifically the inability to recognize sensor information. However, studies by Vairo et al. (2022, 2021) stated that component failures have the highest basic event probability, and Fan et al. (2023) found that excessive ship motion during LNG bunkering is the most influential factor. The difference in results is because human error was not incorporated into their FTA, and the importance of operational and human error has not been explored in LNG bunkering risk analysis studies (Peng et al., 2021).

This study has three key limitations. First, the FTA model adopts a general approach, focusing on factors such as leakage, human error, and pressure. Detailed component-level failures should be included for a more comprehensive failure analysis. Additionally, the human error basic events are broadly categorized; refining them using HFACS, particularly for unsafe acts, would improve the precision of human error assessment. Moreover, organizational factors such as training, drills, and operating procedures should be considered in human-related error analysis. Second, the study relies on expert linguistic judgment for probability estimation. Future research should incorporate near-miss or accident data, particularly from hydrogen-related industries or storage tanks, to enhance analytical accuracy. Third, this study focuses solely on bunkering failures without addressing post-failure consequences, such as fire incidents or the safe dispersion of leaked hydrogen. Therefore, integrating FTA with Event Tree Analysis (ETA) to develop a bow-tie model should be considered in future research.

5. CONCLUSION

The bunkering process of liquefied hydrogen from port to ship is a critical operation; therefore, mapping failure events using FTA and modelling with FBN is necessary. FTA was integrated with FBN by quantifying each basic event based on expert assessment and ranking them using valuation rates and sensitivity analysis of the Bayesian Network. Hydrogen leakage, human error, and overpressure were identified as intermediate events (main failures) in FTA based on a literature review of port-to-ship LH2 bunkering operations. Key findings of this study include:

1. Human factors are critical, with the highest prior probability of failure occurring in basic events related to human activity (Task Execution, followed by Human-Machine Interface Problems, Inadequate skilled personnel, and fatigue).
2. Sensitivity and variation rate analysis show that human-related errors are the most significant contributors to hydrogen bunkering failure.

3. Basic events related to pressure failure have minor significance in the occurrence of the top event.
4. The probability of basic events involving hydrogen leakage is lower than other intermediate events; however, failure of components such as the hose, valve, and manifold increases the probability of top event failure.

Given the paramount importance of human error in hydrogen bunkering failures, stakeholders such as shipping companies and bunkering operators should provide proper training and simulation for the novel technology, combined with an adequate understanding of automation processes. This approach can reduce the probability of failure due to human error in the foreseeable future.

ACKNOWLEDGEMENT

This study was funded by Research Collaboration of The Latest Research and Cooperation Potential on Net Zero Emission In 2024 Batch 3 from New Energy and Industrial Technology Development Organization of Japan (NEDO) grant number 39/II.7/HK/2024 and Authors would like to express gratitude to all experts that contributed their knowledge.

CONFLICT OF INTEREST

Authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

REFERENCES

Aarskog, F.G., Hansen, O.R., Strømgren, T. and Ulleberg, Ø., 2020. Concept risk assessment of a hydrogen driven high speed passenger ferry. International Journal of Hydrogen Energy, 45(2), pp.1359–1372. Available at: https://doi.org/10.1016/j.ijhydene.2019.05.128

Abdin, Z., Khalilpour, K. and Catchpole, K., 2022. Projecting the levelized cost of large scale hydrogen storage for stationary applications. Energy Conversion and Management, 270, 116241. Available at: https://doi.org/10.1016/j.enconman.2022.116241

Adams, M.J., Wadge, M.D., Sheppard, D., Stuart, A. and Grant, D.M., 2024. Review on onshore and offshore large-scale seasonal hydrogen storage for electricity generation: Focusing on improving compression, storage, and roundtrip efficiency. International Journal of Hydrogen Energy, 73, pp.95–111. Available at: https://doi.org/10.1016/j.ijhydene.2024.05.421

Akyuz, E., Arslan, O. and Turan, O., 2020. Application of fuzzy logic to fault tree and event tree analysis of the risk for cargo liquefaction on board ship. Applied Ocean Research, 101, 102238.

Al Ghafri, S.Z.S. et al., 2022. Hydrogen liquefaction: A review of the fundamental physics, engineering practice and future opportunities. Energy & Environmental Science, 15(7), pp.2690–2731. Available at: https://doi.org/10.1039/D2EE00099G

Alavi-Borazjani, S.A., Adeel, S. and Chkoniya, V., 2025. Hydrogen as a sustainable fuel: Transforming maritime logistics. Energies, 18(5), 1231. Available at: https://doi.org/10.3390/en18051231

Aliabadi, M.M., Abbassi, R., Kalatpour, O., Ahmadi, O. and Moshiran, V.A., 2024. Process accident prediction using Bayesian network based on IT2Fs and Z-number: A case study of spherical tanks. PLOS ONE, 19(8), e0307883. Available at: https://doi.org/10.1371/journal.pone.0307883

Aliabadi, M.M., Pourhasan, A. and Mohammadfam, I., 2020. Risk modelling of a hydrogen gasholder using fuzzy Bayesian network (FBN). International Journal of Hydrogen Energy, 45(1), pp.1177–1186.

Animah, I., 2024. Application of Bayesian network in the maritime industry: Comprehensive literature review. Ocean Engineering, 302, 117610. Available at: https://doi.org/10.1016/j.oceaneng.2024.117610

Atehnjia, D.N., Zaili, Y. and Wang, J., 2018. Application of fault tree–Bayesian network for graving dock gate failure analysis. International Journal of Advance in Scientific Research and Engineering, 4(1), pp.27–37. Available at: https://doi.org/10.7324/ijasre.2018.32576

Aziz, M., 2021. Liquid hydrogen: A review on liquefaction, storage, transportation, and safety. Energies. Available at: https://doi.org/10.3390/en14185917

Barthélémy, H., 2012. Hydrogen storage – Industrial perspectives. International Journal of Hydrogen Energy, 37(22), pp.17364–17372. Available at: https://doi.org/10.1016/j.ijhydene.2012.04.121

Birch, D., Miller, E. and Bradley, T., 2023. Human reliability analysis using a human factors hazard model. Journal of System Safety, 58(2), pp.7–29. Available at: https://doi.org/10.56094/jss.v58i2.251

Bobbio, A., Portinale, L., Minichino, M. and Ciancamerla, E., 2001. Improving the analysis of dependable systems by mapping fault trees into Bayesian networks. Reliability Engineering and System Safety, 71, pp.249–260.

Borgheipour, H., Tehrani, G.M., Eskandari, T., Mohammadieh, O.C. and Mohammadfam, I., 2021. Dynamic risk analysis of hydrogen gas leakage using bow-tie technique and Bayesian network. International Journal of Environmental Science and Technology, 18(11), pp.3613–3624. Available at: https://doi.org/10.1007/s13762-020-03090-4

Bulat, H.H., Kaymakçı, Ö.T. and Ilhan, H., 2024. Human factors in hydrogen storage: An analysis of safety implications. International Journal of Hydrogen Energy. Available at: https://doi.org/10.1016/j.ijhydene.2024.07.295

Butt, J.A. and Markmiller, J.F.C., 2025. Hydrogen properties and their safety implications for experimental testing of wing structure-integrated hydrogen tanks. Energies, 18(8). Available at: https://doi.org/10.3390/en18081930

Calabrese, M. et al., 2024. Hydrogen safety challenges: A comprehensive review on production, storage, transport, utilization, and CFD-based consequence and risk assessment. Energies, 17(6), 1350. Available at: https://doi.org/10.3390/en17061350

Campari, A. et al., 2024. Risk-based inspection and maintenance of a liquid hydrogen bunkering facility. Proceedings of the International Conference on Offshore Mechanics and Arctic Engineering (OMAE), 2. Available at: https://doi.org/10.1115/OMAE2024-121761

Cava, C., Gagliardi, G.G., Piscolla, E. and Borello, D., 2025. Techno-economic analysis of hydrogen transport via truck using liquid organic hydrogen carriers. Available at: https://doi.org/10.20944/preprints202502.1311.v1

Cem, A., Akyuz, E. and Arslan, O., 2019. Application of fuzzy fault tree analysis (FFTA) to maritime industry: A risk analysis of ship mooring operation. Ocean Engineering, 179, pp.128–134. Available at: https://doi.org/10.1016/j.oceaneng.2019.03.029

Chen, S.-J. and Hwang, C.-L., 1992. Fuzzy multiple attribute decision making methods. In: Fuzzy multiple attribute decision making: Methods and applications. Springer, pp.289–486.

EMSA, 2022. European maritime safety report. Available at: https://doi.org/10.2808/138925

Fan, H., Enshaei, H. and Jayasinghe, S.G., 2023. Dynamic quantitative risk assessment of LNG bunkering SIMOPs based on Bayesian network. Journal of Ocean Engineering and Science, 8(5), pp.508–526. Available at: https://doi.org/10.1016/j.joes.2022.03.004

France, M.E., 2017. Engineering for humans: A new extension to STPA. Massachusetts Institute of Technology.

Gabov, A.V. and Lizikova, M.S., 2022. Hydrogen energy: Legal support and international cooperation. Herald of the Russian Academy of Sciences, 92(5), pp.S612–S626. Available at: https://doi.org/10.1134/S1019331622130020

Genovese, M., Blekhman, D. and Fragiacomo, P., 2024. An exploration of safety measures in hydrogen refueling stations. Hydrogen, 5(1), pp.102–122. Available at: https://doi.org/10.3390/hydrogen5010007

Giannis, S., Salmeron-Perez, N. and Spetsieris, N., 2023. Challenges in realising composite liquid hydrogen cryogenic storage. Available at: https://doi.org/10.47120/npl.MAT114

Hänninen, M., 2014. Bayesian networks for maritime traffic accident prevention: Benefits and challenges. Accident Analysis and Prevention, 73, pp.305–312. Available at: https://doi.org/10.1016/j.aap.2014.09.017

Hansen, O.R., 2020. Hydrogen infrastructure—Efficient risk assessment and design optimization approach. Process Safety and Environmental Protection, 143, pp.164–176. Available at: https://doi.org/10.1016/j.psep.2020.06.028

Hosseini, S.E. and Butler, B., 2020. An overview of development and challenges in hydrogen powered vehicles. International Journal of Green Energy, 17(1), pp.13–37

Hsu, H.-M. and Chen, C.-T., 1996. Aggregation of fuzzy opinions under group decision making. Fuzzy Sets and Systems, 79.

Jeon, S., Jeong, S. and Nam, D., 2023. A study on the establishment of bunkering safety zone for hydrogen propulsion ships in coastal area. Journal of the Society of Naval Architects of Korea, 60(6), pp.433–440.

Jiang, M., Lu, J., Yang, Z., Li, J. and Jiang, M., 2020. Risk analysis of maritime accidents along the main route of the Maritime Silk Road: A Bayesian network approach. Maritime Policy & Management. Available at: https://doi.org/10.1080/03088839.2020.1730010

Joung, T.-H., Kang, S.-G., Lee, J.-K. and Ahn, J., 2020. The IMO initial strategy for reducing greenhouse gas emissions and its follow-up actions towards 2050. Journal of International Maritime Safety, Environmental Affairs, and Shipping, 4(1), pp.1–7.

Kang, D.-H., An, J.-H. and Lee, C.-J., 2023. Optimization of thermal insulation for liquid hydrogen storage tanks. Available at: https://doi.org/10.2139/ssrn.4507712

Kharchenko, V., Brezhniev, E., Sklyar, V. and Boyarchuk, A., 2013. Critical infrastructures safety assessment combining fuzzy models and Bayesian belief network under uncertainties. In: pp.245–254. Available at: https://doi.org/10.1007/978-3-319-00945-2_22

Kuzu, A.C., Akyuz, E. and Arslan, O., 2019. Application of fuzzy fault tree analysis (FFTA) to maritime industry: A risk analysis of ship mooring operation. Ocean Engineering, 179, pp.128–134.

Lavasani, S.M., Zendegani, A. and Celik, M., 2015. An extension to fuzzy fault tree analysis application in petrochemical process industry. Process Safety and Environmental Protection, 93, pp.75–88. Available at: https://doi.org/10.1016/j.psep.2014.05.001

Li, G., Zhang, H., Li, S. and Zhang, C., 2025. Risk assessment of hydrogen fuel system leakage in ships based on noisy-OR gate model Bayesian network. Journal of Marine Science and Engineering, 13(3), pp.1–19. Available at: https://doi.org/10.3390/jmse13030523

Li, P., Wang, Y. and Yang, Z., 2024. Risk assessment of maritime autonomous surface ships collisions using an FTA-FBN model. Ocean Engineering, 309, 118444. Available at: https://doi.org/10.1016/j.oceaneng.2024.118444

Li, X., Liu, W., Zhou, N. and Yuan, X., 2025. Probability analysis of hazardous chemicals storage tank leakage accident based on neural network and fuzzy dynamic fault tree. Applied Sciences, 15(7). Available at: https://doi.org/10.3390/app15073504

Majumdar, A., Deutch, J.M., Prasher, R.S. and Griffin, T.P., 2021. A framework for a hydrogen economy. Joule, 5(8), pp.1905–1908. Available at: https://doi.org/10.1016/j.joule.2021.07.007

Meel, A. and Seider, W.D., 2007. Real-time risk analysis of safety systems. Computers & Chemical Engineering, 32(4–5), pp.827–840. Available at: https://doi.org/10.1016/j.compchemeng.2007.03.006

Mekonnin, A.S., Wacławiak, K., Humayun, M., Zhang, S. and Ullah, H., 2025. Hydrogen storage technology and its challenges: A review. Catalysts, 15(3), 260. Available at: https://doi.org/10.3390/catal15030260

Naquash, A., Riaz, A., Qyyum, M.A., Aziz, M., Assareh, E. and Lee, M., 2023. Liquid hydrogen storage and regasification process integrated with LNG, NGL, and liquid helium production. Renewable Energy, 213, pp.165–175. Available at: https://doi.org/10.1016/j.renene.2023.05.122

Nerheim, A.R., Æsøy, V. and Holmeset, F.T., 2021. Hydrogen as a maritime fuel—Can experiences with LNG be transferred to hydrogen systems? Journal of Marine Science and Engineering, 9(7). Available at: https://doi.org/10.3390/jmse9070743

Nicolis, J.S. and Tsuda, I., 1985. Chaotic dynamics of information processing: The “magic number seven plus-minus two” revisited. Bulletin of Mathematical Biology, 47(3), pp.343–365.

Onisawa, T., 1988. A representation of human reliability using fuzzy concepts. Information Sciences, 45(2), pp.153–173.

Peng, Y., Zhao, X., Zuo, T., Wang, W. and Song, X., 2021. A systematic literature review on port LNG bunkering station. Transportation Research Part D: Transport and Environment, 91. Available at: https://doi.org/10.1016/j.trd.2021.102704

Preuster, P., Alekseev, A. and Wasserscheid, P., 2017. Hydrogen storage technologies for future energy systems. Annual Review of Chemical and Biomolecular Engineering, 8(1), pp.445–471. Available at: https://doi.org/10.1146/annurev-chembioeng-060816-101334

Pristrom, S., Yang, Z., Wang, J. and Yan, X., 2016. A novel flexible model for piracy and robbery assessment of merchant ship operations. Reliability Engineering and System Safety, 155, pp.196–211. Available at: https://doi.org/10.1016/j.ress.2016.07.001

Qiao, W., Liu, Y., Ma, X. and Liu, Y., 2020a. A methodology to evaluate human factors contributing to maritime accidents by mapping fuzzy fault tree into ANN based on HFACS. Ocean Engineering, 197, 106892. Available at: https://doi.org/10.1016/j.oceaneng.2019.106892

Qiao, W., Liu, Y., Ma, X. and Liu, Y., 2020b. Human factors analysis for maritime accidents based on a dynamic fuzzy Bayesian network. Risk Analysis, 40(5), pp.957–980. Available at: https://doi.org/10.1111/risa.13444

Sakar, C., Toz, A.C., Buber, M. and Koseoglu, B., 2021. Risk analysis of grounding accidents by mapping a fault tree into a Bayesian network. Applied Ocean Research, 113, 102764. Available at: https://doi.org/10.1016/j.apor.2021.102764

Schiaroli, A., Cozzani, V. and Ustolin, F., 2024. Consequence analysis of a bunkering facility for liquid hydrogen loading and unloading. Available at: http://asmedigitalcollection.asme.org/OMAE/proceedings-pdf/OMAE2024/87790/V002T02A070/7360740/v002t02a070-omae2024-126787.pdf

Semchukova, V., Polemis, K., Abdin, Z., Solanki, B. and Cary, S., 2024. Hydrogen infrastructure analysis for port applications. National Renewable Energy Laboratory (NREL).

Sezer, S.I. et al., 2024. Analyzing human reliability for cargo oil pump operation using fuzzy CREAM extended Bayesian network. Ocean Engineering, 299, 117345. Available at: https://doi.org/10.1016/j.oceaneng.2024.117345

Shappell, S. and Wiegmann, D., 2003. A human error analysis of general aviation controlled flight into terrain accidents occurring between 1990–1998.

Skiba, S., 2024. Environmental management in a seaport in the context of sustainable development challenges. European Research Studies Journal, 27(1), pp.1–10.

Sugeno, M., 1999. On stability of fuzzy systems expressed by fuzzy rules with singleton consequents. IEEE Transactions on Fuzzy Systems, 7(2), pp.201–224.

Sumon, M.M.A., Kim, H., Na, S., Choung, C. and Kjønsberg, E., 2024. Systems-based safety analysis for hydrogen-driven autonomous ships. Journal of Marine Science and Engineering, 12(6). Available at: https://doi.org/10.3390/jmse12061007

Tamburini, F., Iaiani, M. and Cozzani, V., 2025. Analysis of system resilience in escalation scenarios involving LH2 bunkering operations. Reliability Engineering and System Safety, 257. Available at: https://doi.org/10.1016/j.ress.2025.110816

Tamburini, F., Ustolin, F., Cozzani, V. and Paltrinieri, N., 2024. Performance assessment of safety barriers in liquid hydrogen bunkering operations using Bayesian network. Proceedings of the ASME 2024 43rd International Conference on Ocean, Offshore and Arctic Engineering (OMAE 2024). Available at: https://doi.org/10.1115/OMAE2024-126832

Töz, A., Büber, M., Köseoğlu, B. and Şakar, C., 2022. Analysis of collision accidents in maritime transportation by FTA method. Turkish Journal of Maritime and Marine Sciences, 8(1), pp.15–30.

Tsunemi, K., Kihara, T., Kato, E., Kawamoto, A. and Saburi, T., 2019. Quantitative risk assessment of the interior of a hydrogen refueling station considering safety barrier systems. International Journal of Hydrogen Energy, 44(41), pp.23522–23531. Available at: https://doi.org/10.1016/j.ijhydene.2019.07.027

Usman, M.R., 2022. Hydrogen storage methods: Review and current status. Renewable and Sustainable Energy Reviews, 167, 112743. Available at: https://doi.org/10.1016/j.rser.2022.112743

Vairo, T., Benvenuto, A.C., Tedeschi, A., Reverberi, A.P. and Fabiano, B., 2022. Make bow-tie dynamic by rethinking it as a hierarchical Bayesian network: Dynamic risk assessment of an LNG bunkering operation. Chemical Engineering Transactions, 91, pp.277–282. Available at: https://doi.org/10.3303/CET2291047

Vairo, T., Gualeni, P., Reverberi, A.P. and Fabiano, B., 2021. Resilience dynamic assessment based on precursor events: Application to ship LNG bunkering operations. Sustainability, 13(12). Available at: https://doi.org/10.3390/su13126836

Ventikos, N.P., Koimtzoglou, A., Drivas, D., Podimatas, V.C. and Kopsacheilis, I., 2023. A priority-based failure mode and effects analysis (FMEA) method for risk assessment of hydrogen applications onboard maritime vessels.

Villa, V., Paltrinieri, N., Khan, F. and Cozzani, V., 2016. Towards dynamic risk analysis: A review of the risk assessment approach and its limitations in the chemical process industry. Safety Science, 89, pp.77–93. Available at: https://doi.org/10.1016/j.ssci.2016.06.002

Visser, K., Baldi, F. and van Biert, L., 2020. Editorial of special issue on maritime hydrogen. International Shipbuilding Progress, 67(1), pp.1–3. Available at: https://doi.org/10.3233/ISP-209002

Wan, C., Yan, X., Zhang, D., Qu, Z. and Yang, Z., 2019. An advanced fuzzy Bayesian-based FMEA approach for assessing maritime supply chain risks. Transportation Research Part E, 125, pp.222–240. Available at: https://doi.org/10.1016/j.tre.2019.03.011

Wang, H. and Miller, D.C., 2016. Thermal management and enhancement of adsorption-based onboard hydrogen storage system. In: Proceedings of the ASME 2016 Energy Sustainability Conference. Available at: https://doi.org/10.1115/ES2016-59629

Wang, W.J., 1997. New similarity measures on fuzzy sets and on elements. Fuzzy Sets and Systems, 85(3), pp.305–309. Available at: https://doi.org/10.1016/0165-0114(95)00365-7

Wang, X. and Gao, W., 2023. Hydrogen leakage risk assessment for hydrogen refueling stations. International Journal of Hydrogen Energy, 48(91), pp.35795–35808. Available at: https://doi.org/10.1016/j.ijhydene.2023.05.340

Wang, Z., Gui, X., Wang, W., Zhao, X. and Ji, X., 2025. Gas pipeline leakage risk analysis based on dynamic Bayesian network. Processes, 13(4). Available at: https://doi.org/10.3390/pr13040927

Waskito, D.H., Bowo, L.P., Puriningsih, F.S., Muhtadi, A. and Kurniawan, I., 2024. Comprehensive analysis of ship sinking accidents using Bayesian network. Australian Journal of Maritime and Ocean Affairs, pp.1–24. Available at: https://doi.org/10.1080/18366503.2024.2389679

Waskito, D.H., Kurt, R.E., Gusti, A.P. and Bowo, L.P., 2025. Assessing the risk of transporting battery electric vehicles through water transportation modes using Bayesian network approach. Ocean Engineering, 341, 122606. Available at: https://doi.org/10.1016/j.oceaneng.2025.122606

Yang, C. and Mott, J.H., 2020. HFACS analysis of U.S. general aviation accidents using Bayesian network. Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 64(1), pp.1655–1659. Available at: https://doi.org/10.1177/1071181320641403

Zadeh, L.A., 1965. Fuzzy sets. Information and Control, 8(3), pp.338–353.

Zarei, E., 2019. A hybrid model for human factor analysis in process accidents: FBN-HFACS. Journal of Loss Prevention in the Process Industries, 57, pp.142–155. Available at: https://doi.org/10.1016/j.jlp.2018.11.015

Zhang, H. and Jiang, D., 2023. Risk analysis of fire in hydrogen storage system of ship hydrogen fuel cell based on FSA. Proceedings of the IEEE International Conference on Transportation Information and Safety (ICTIS 2023), pp.2480–2490. Available at: https://doi.org/10.1109/ICTIS60134.2023.10243733

Zhang, J. et al., 2024. Dynamic risk evaluation of hydrogen station leakage based on fuzzy dynamic Bayesian network. International Journal of Hydrogen Energy, 50, pp.1131–1145. Available at: https://doi.org/10.1016/j.ijhydene.2023.10.005

Zhao, C., Wu, B., Yip, T.L. and Lv, J., 2021. Use of fuzzy fault tree analysis and noisy-or gate Bayesian network for navigational risk assessment in Qinzhou port. TransNav, 15(4), pp.765–771. Available at: https://doi.org/10.12716/1001.15.04.07

Zhao, C., Yip, T.L., Wu, B. and Lyu, J., 2022. Use of fuzzy fault tree analysis and Bayesian network for occurrence likelihood estimation of navigational accidents in Qinzhou port. Ocean Engineering, 263. Available at: https://doi.org/10.1016/j.oceaneng.2022.112381

Zhou, Q., Wong, Y.D., Loh, H.S. and Yuen, K.F., 2018. A fuzzy and Bayesian network CREAM model for human reliability analysis: The case of tanker shipping. Safety Science, 105, pp.149–157. Available at: https://doi.org/10.1016/j.ssci.2018.02.011

Zhou, Y., Li, X. and Yuen, K.F., 2022. Holistic risk assessment of container shipping service based on Bayesian network modelling. Reliability Engineering and System Safety, 220, 108305. Available at: https://doi.org/10.1016/j.ress.2021.108305

APPENDIX

The details of the Intermediate events

Identifier	Intermediate Events
IE1	Hose Failure
IE2	Valve/ Connector Failure
IE3	Adverse weather
IE4	Dropped Object
IE5	Uncontrollable Transfer Rate
IE6	Mechanical Failure
IE7	Purging Gas Failure
IE8	Improper Purging
IE9	Thermal Expansion
IE10	Hydrogen Leakage
IE11	Human Error
IE12	Pressure Failure
IE13	Failure of Bunkering Pump Operation