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RESEARCH ARTICLE

Risk Assessment of Solid Bulk Cargo Liquefaction Consequences in Maritime Transportation under a Fuzzy Bayesian Network Approach

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ABSTRACT

Solid bulk cargo liquefaction is hazardous for bulk carrier ships as they reduce the stability of the ship. Most dry bulk ship owners face solid bulk cargo liquefaction during the carriage of ore cargoes. The consequences of cargo liquefaction could have catastrophic effects such as the ship sinking or capsizing. To improve the process of safety during the shipment of bulk cargo and reduce potential consequences, a detailed risk analysis is needed. The purpose of this paper is to conduct a systematic probabilistic risk analysis of the liquefaction of solid bulk cargo in the marine sector in order to allay this concern in order to deal with complex causation and uncertainty resulting from complex interdependence among risk factors, limited data, and a complex environment. A Bayesian network (BN) method under fuzzy logic has been utilized in the research. Whilst the BN enables us to calculate the conditional probability of each basic event in the graph, the fuzzy logic tackles uncertainty and the vagueness of expert judgment. The findings of the paper will assist solid bulk cargo owners and shippers in reducing the risk of solid bulk cargo liquefaction during maritime transportation.

Keywords: Maritime transportation, Cargo liquefaction, Fuzzy logic, Probabilistic risk assessment, Bayesian Network.

1. Introduction

The definition of risk is the combination of the probability of hazards and the severity of that consequence (Goerlandt et al., 2015). The risk investigated in the article is the liquefaction of dry cargo carried on board. Shipmasters are likely to be aware of the risk of liquefaction associated with the cargo they are carrying on board. But it is unclear to know the extent of the damage, the environment, and how human life will be affected after the cargo it carries liquefies. Therefore, risk analysis of consequences plays a crucial role in different hazardous operations such as cargo handling, cargo transferring, etc. (Akyuz et al., 2020). Risk-based studies have been expanding in marine transportation with the use of both qualitative and quantitative risk assessment approaches. Risk-based methodologies such as the Failure Mode Effect Analysis (FMEA), Hazard and Operability study (HAZOP), Fault Tree Analysis (FTA), Bow-Tie, and the Bayesian Network have been cited in maritime transportation literature (Sarıalioğlu et al., 2020; Aydin et al., 2021a; Kaptan, 2021a; Akyuz & Celik, 2018; Aziz et al., 2019). Since the Bayesian Network (BN) technique can present conditional dependency by nodes in a directed graph, it has recently been used by many safety researchers to quantitatively identify risks. The Bayesian Network has been used by many authors in their research on different subjects in maritime research (Sakar et al., 2020; Kaptan, 2021b; Çakir et al., 2021; Özaydın et al., 2022; Aydin and Kamal, 2022).

The topic, solid bulk cargo liquefaction due to the presence of excess moisture and the motions of the ship, has not gained a sufficient level of attention in the maritime sector since the consequences of solid bulk cargo liquefaction may create life-threatening conditions. In terms of safety and risk analysis, there is a lack of studies that deal specifically with the phenomenon of cargo liquefaction. Therefore, this paper prompts a comprehensive probabilistic risk analysis of solid bulk cargo liquefaction to improve the process of safety in bulk cargo and reduce risks.

Since there is a lack of studies in the literature to address the above-mentioned constraint, this work contributes to the body of knowledge by addressing epistemic uncertainty. Furthermore, solid bulk cargo liquefaction consequences in maritime transportation involve significant risks. However, in the literature review, no comprehensive study has been found that makes solid bulk cargo liquefaction consequences risk analysis in maritime transportation with an improved Bayesian Network with a fuzzy

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logic approach. The BN is widely used in risk analysis and is a simulation of complicated system faults (Li et al., 2016). The BN is applied to examine potential failure problems, and fuzzy logic overcomes the ambiguity of expert evaluations.

In this context, the paper is organized as follows. This section gives a general assessment of the literature, and comprehensive information on the phenomenon of bulk cargo liquefaction while section 2 explains the method. The probabilistic risk analysis for solid bulk cargo liquefaction's consequences is performed in Section 3. Section 4 presents the findings of the research. Finally, section 5 gives the conclusions of the research.

1.1. Solid bulk cargo liquefaction phenomenon on-board ship

Cargo liquefaction is a quick transition of cargo-forming particles from a stable solid state to a viscous liquid form (Jonas, 2010). In such cases, the cargo loses shear strength due to the particle's loss of contact and behaves more like a liquid than a solid (IMO, 2012). For this reason, liquefaction is a significant difficulty for the transportation of ore cargoes such as iron and nickel. The cargo liquefaction may reduce the stability of ships due to the Free Surface Effect (FSE). Also, the loss of stability (reduction or loss of GM) leads the vessel to list at a dangerous angle to one side. In some cases, the angle of the heel continues to increase, resulting in the vessel listing heavily down, flooding or capsizing, and inducing the loss of the vessel, commodity, and crew.

Cargo liquefaction can be partially prevented by tests before loading. The TML (Transportable Moisture Limit) value indicates the maximum amount of moisture that the cargo can transport safely. There are three laboratory test methods used to measure the TML value: the flow table test, the penetration test, and the proctor test. Each test method is suitable for different types of cargo. (DNV-GL, 2015). Therefore, competent experts should be consulted for method selection. The "can test", which is used to approximate the probability of the flow of load, is a supplement for laboratory tests rather than a substitute. The margin of error is quite high in this test applied by the ship's captain. Although these tests give an idea of the moisture content of the load, they are likely to fail, because a test to determine the transportable moisture limit of a solid bulk cargo must be carried out within seven days before the loading date. As the time interval between test and loading increases, the margin of error increases. Also, if the environment where the cargo is stored is humid, the amount of moisture may increase after the test. Moreover, consignments originating from different stockpiles might have been mined separately and under varying conditions. Tests may give incorrect results if different stockpiles are not evaluated separately. Finally, the tests are highly dependent on the competence of the person conducting the test.

Numerous accidents have occurred due to cargo liquefaction in dry bulk transportation, and these accidents continue to result in the loss of seafarers (DNV-GL, 2015). Table 1 shows some accidents due to solid bulk cargo liquefaction (DNV-GL, 2019). There were 8 casualties of suspected cargo liquefaction among 39 cases between 2009 and 2019. The highest loss of life has been attributed to cargo shifting (liquefaction). A total of 106 lives were lost or 61.3% of the total loss of life was caused by 8 casualties. Also, when the 2018 and 2019 data are compared, it is seen that the rate of loss of life due to bulk cargo liquefaction increased from 53.7% to 61.3% (INTERCARGO, 2019).

Table 1. Accidents due to solid bulk cargo liquefaction (DNV-GL, 2019)

Vessel name	Dwt	Built	Loss of life	Loss of Vessel	Year	Cargo type	Area
Asian Forest	16k	2007	0	Yes	2009	Iron ore	India
Black Rose	39k	1977	1	Yes	2009	Iron ore	India
Jian Fu Star	45k	1983	13	Yes	2010	Nickel ore	Indonesia
Nasco Diamond	57k	2009	22	Yes	2010	Nickel ore	Indonesia
Hong Wei	50k	2001	10	Yes	2010	Nickel ore	Indonesia
Bright Rubby	27k	1987	6	Yes	2011	Nickel ore	Hong Kong
Vinalines Queen	56k	2005	22	Yes	2011	Nickel ore	Philippines
Sun Spirits	11k	2007	0	Yes	2012	Iron ore	Philippines
Anna Bo	57k	2009	0	Listing	2013	Nickel ore	Philippines
Harita Bauxite	50k	1983	15	Yes	2013	Nickel ore	Indonesia
Trans Summer	57k	2012	0	Yes	2013	Nickel ore	Philippines
Alam Manis	56k	2007	1	Listing	2015	Nickel ore	Philippines
Bulk Jupiter	56k	2009	18	Yes	2015	Bauxite	Malaysia
Emerald Star	57k	2010	10	Yes	2017	Nickel ore	Philippines
Nur Allya	52k	2002	25	Yes	2019	Nickel ore	Indonesia

2. Methodology

The main concepts of fuzzy logic and the Bayesian belief network are presented in this section. Figure 1 depicts the theoretical structure of the methodology.

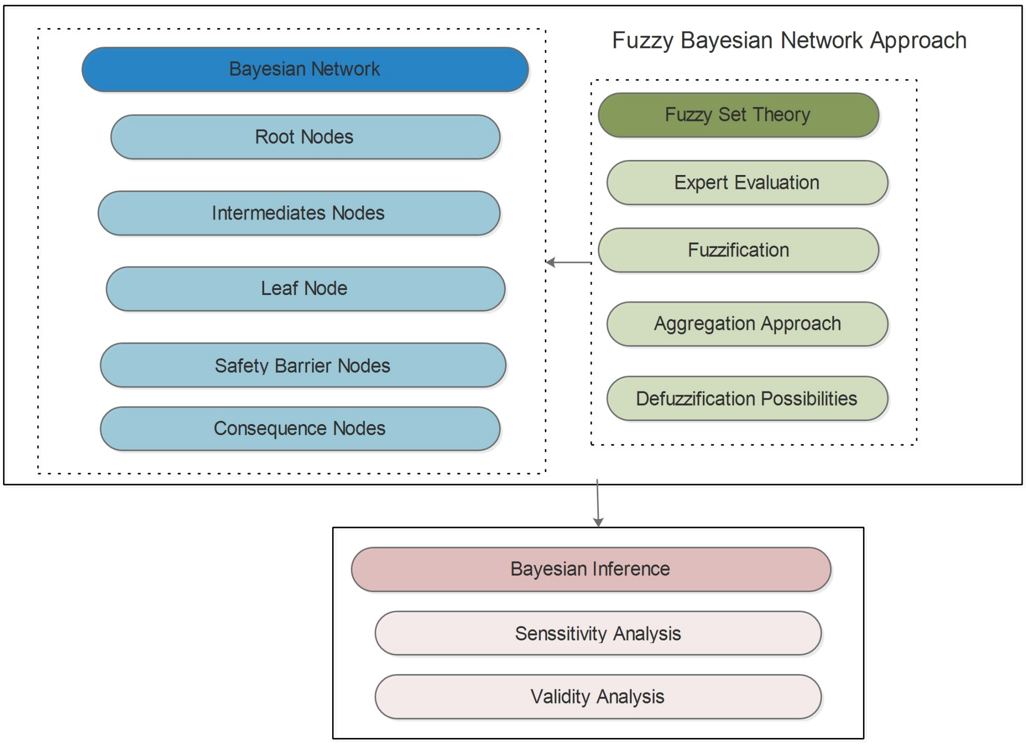

Figure 1. Conceptual framework of the Fuzzy Bayesian Network approach

2.1. Bayesian network

The BN is an efficient and flexible graphical model that illustrates the probabilistic correlations between variables. (Uğurlu et al., 2022). In the BN method, variables are represented as nodes in an oriented acyclic network, while conditional dependency between variables are represented by directional links (Şakar and Zorba, 2017). The network is represented graphically by nodes that represent the variables and directed arrows that represent their probabilistic causal dependency between them.

The probability tables include conditional probabilities as well as posterior probabilities for the variables in the network structure are managed by the quantitative part of the BN.

The Bayes Network's base is the Chain Rule, which addresses the joint probability distributions of variables. The marginal and conditional probabilities for each network node can be calculated using the chain rule. The joint probability of the variable Xi is given in the following equations if U= $X_1, X_2 ..., X_n$ are variables (Jensen and Nielsen, 2007).

$$P(U) = \prod_{i=1}^{n} P(X_i|P_\alpha(X_i)) \tag{1}$$

Where $P_\alpha(X_i)$ is the parent set of variables and j≠i . The probability of Xi is calculated as:

$$P(X_i) = \sum_{x_j} P(U) \tag{2}$$

The Bayes theorem, utilized by the BN to calculate the posterior probabilities of events given updated observations, also known as evidence (E), in the form of incident occurrence, as stated by equation 3, is used to determine the likelihood that certain occurrences will occur (Kerner and Herrtwich, 2001).

$$P(U \setminus E) = \frac{P(U,E)}{P(E)} = \frac{P(U,E)}{\sum_u P(U,E)} \tag{3}$$

Where U is the universe of variables $X_1, X_2 . . . , X_n$

2.2. Bayesian network under fuzzy logic environment

It is mentioned that there are numerous methods, including statistical data, literature reviews, etc., for determining the prior and conditional probability of the nodes. If there is a lack of data or a high level of ambiguity in the statistical data or associated literature, fuzzy set theory can be used to reduce uncertainty by using linguistic values. A Fuzzy Bayesian Network (FBN) has been designed to derive the probability values of the nodes in the Bayesian network.

2.2.1. ***Expert elicitation***

The probabilities must be established in order to calculate the cargo liquefaction risk probability (leaf node) and the significance of nodes. The expert elicitation approach offers a solution and useful information for risk assessment. An expert is someone who has extensive training and expertise regarding the functioning of the system (Rajakarunakaran et al., 2015). The study involves experts at various levels, each bringing their own expertise, educational background, and professional experience.

As a result, experts may express various viewpoints on the same occurrences and offer subjectively differing assessments. At this point, the significance of each expert influences judgments of heterogeneous groupings of experts. An expert weighting score was employed by Senol et al. (2015) to illustrate the relative level of the experts. To get expert opinions for each node, linguistic phrases might be employed to make expert judgments. The ideal range for linguistic term selection is between 5 and 9, which will allow experts to make good judgments (Rajakarunakaran et al., 2015; Lavasani et al., 2012; Miller, 1956). The numerical approach method is used in the suggested method to translate the language phrases of marine professionals into trapezoidal fuzzy values.

Within this scope, Figure 2 shows ratings and membership functions of fuzzy sets.

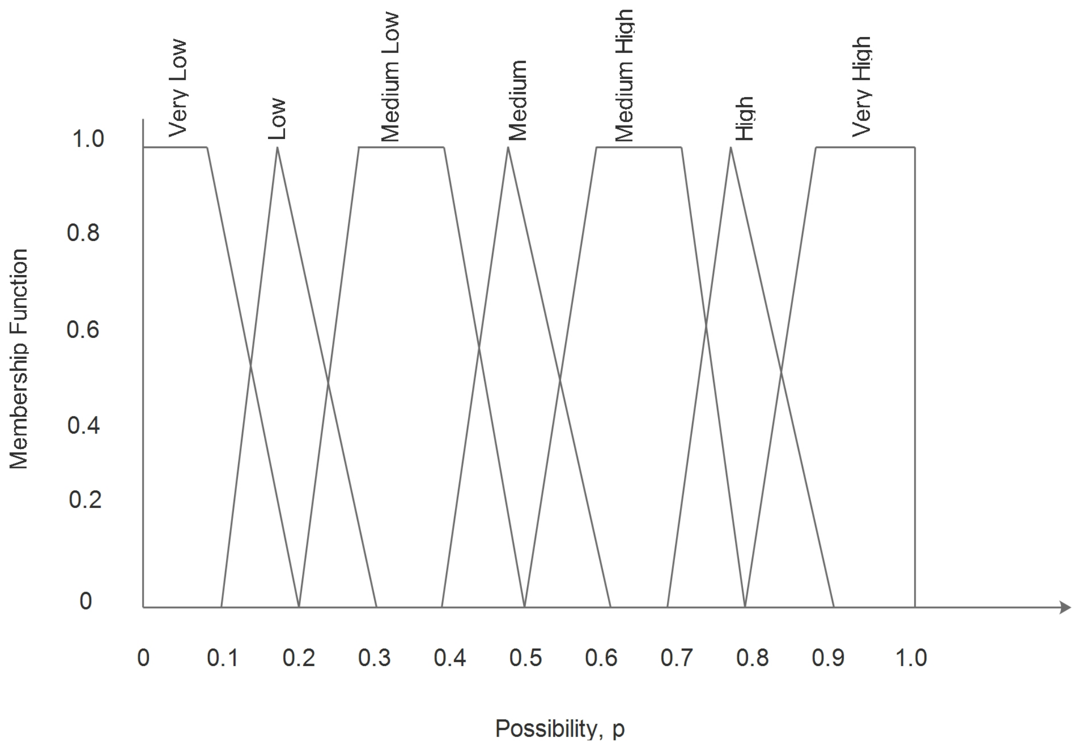

Figure 2. Fuzzy rating and membership functions

2.2.2. *Fuzzy possibility*

The fuzzy sets are extensions and simplified forms of a traditional set of numbers. In fuzzy logic, a fuzzy subset A is qualified by a membership function that is correlated with each element x in the universe X to the real number in the interval [0, 1] (Zadeh, 1965). The equation μ_A (x) illustrates the membership of x in the fuzzy set A (Zarei et al., 2019; Akyuz et al., 2018) . The membership function μ_A (x) for the trapezoidal fuzzy set numbers (a,b,c,d)can be defined as:

$$\gamma = \begin{cases} 0, & \chi < \alpha \\ \frac{(x-a)}{b-a}, & \alpha \leq \chi \leq b \\ 1, & b \leq \chi \leq c \\ \frac{(d-x)}{d-c}, & c \leq \chi \leq d \\ 0, & \chi > d \end{cases} \tag{4}$$

The fuzzy possibility score (FPs) is a crisp value that represents the experts' aggregated belief of the most likely score to indicate that an event may occur. Experts' judgments in the form of linguistic expressions that aggregated trapezoidal fuzzy numbers are converted into FPs under a fuzzy environment.

The linear opinion pool is an appealing approach to the aggregation of fuzzy possibility distributions. (Clemen & Winkler, 1999):

$$M_i = \sum_{i=1}^{m} W_j A_{ij} = 1, 2, \ldots, n \tag{5}$$

M_i is the fuzzy failure possibility representing the aggregated fuzzy value of event i,
W_j is the weighting score of experts j,
A_{ij} is the linguistic value obtained from expert j about event i,
m is the total number of events while n is the total number of experts.

The linear opinion pool is easily understandable and computable as it is a weighted linear combination of experts' judgments. The weighting factors of heterogeneous marine experts who participated in the survey are calculated according to Table 2 (Senol et al., 2015; Lavasani et al., 2015).

Table 2. Weighting scores of non-homogenous experts

Group	Classification	Score
Professional position	Academician	5
	Operation manager	4
	Deck inspector	3
	Master	2
	Chief Officer	1
Sea service time	≥ 16 years	5
	11-15	4
	6-10	3
	3-5	2
	≤ 3	1
Education Level	PhD	5
	Master	4
	Bachelor	3
	HND	2
	School level	1
Shore service time	≥ 26	5
	16-25	4
	11-15	3
	6 – 10	2
	≤ 5	1

Equations (6) and (7) are used to determine expert weights by determining expert weight scores and expert weight factors (Lavasani et al., 2012).

$$\begin{aligned} \textit{Weight Score of Expert i} &= \textit{Score of Profesional Position of Expert i} \\ &+ \textit{Score of Sea Service Time of Expert i} \\ &+ \textit{Score of Education Level of Expert i} \\ &+ \textit{Score of Shore Service Time of Epert i} \end{aligned} \tag{6}$$

$$\textit{Weight factor of Expert i} = \frac{WeightScoreofExperti}{\sum_{i=1}^{n} WeightScoreofExperti} \tag{7}$$

2.2.3. ***Defuzzification***

The aggregated trapezoidal fuzzy numbers are transformed into FPs in a fuzzy environment during the defuzzification process. Defuzzification methods include mean max membership, centroid method, weighted average method, center of largest area and center of sums (Wang, 1997). In this study, fuzzy possibility values of each basic event were calculated by using the most preferred center of area method because of its simplicity and comprehensibility (Lavasani et al., 2015). This technique was developed by Sugeno (1985).

$$X^* = \frac{\int u_i(\chi)\chi d\chi}{\int u_i(\chi)} \tag{8}$$

X^* is the defuzzified output i,
u_i(X) is the aggregated membership function,
χ is the output variable.

The obtained fuzzy possibilities are assigned as failure probabilities of the events and safety barriers in the developed BN model.

3. Probabilistic risk analysis of solid bulk cargo liquefaction in maritime transportation

For the stability of the vessels, the consequences of cargo liquefaction are extremely detrimental and catastrophic. As a result, the Fuzzy Bayesian Network technique was utilized to conduct a detailed risk analysis for the onboard liquefaction of solid bulk cargo.

3.1. Quantitative risk analysis of cargo liquefaction on-board ship

Due to a lack of data in the maritime industry, expert evaluation is utilized to characterize risk analysis for solid bulk cargo liquefaction. Six marine experts participated in the research. The experts were experienced in dry bulk cargo shipping, particularly for ore and mineral cargoes.

The root events that initiate cargo liquefaction onboard ships are partly taken from the articles (Akyuz et al., 2020) and P&I Club circulars. In addition, past accident results and information taken from face-to-face interviews with experts are used to determine possible consequences (INTERCARGO, 2019). The Bayesian Network is created by brainstorming meetings with maritime experts after identifying the underlying causes and effects. The scenario is depicted in the diagram, starting with the potential root causes of cargo liquefaction, and concluding with potential outcomes depending on whether safety barriers are successful or failures. Table 3 gives definitions of nodes and safety barriers. Figure 3 illustrates a BN diagram created by GeNIe program (BayesFusion, LLC).

Since the sample of maritime experts who responded to the survey was heterogeneous, it was necessary to use equations to explain the relative weight of each judgment (6-7).

Equations (5 - 8) are used for aggregate and defuzzified fuzzy numbers to calculate the fuzzy possibility of root events, safety barriers, and severity of consequences. Table 4 demonstrates the fuzzy possibilities of root events obtained by experts' evaluation. The findings of the failure potentials of safety barriers in the risk of cargo liquefaction are presented in Table 5. Table 6 illustrates the conditional probability of loading wet/humid cargo.

Table 3. Definitions of nodes and safety barriers

No	Nodes	Definitions
1	Independent survey	For the measurement of moisture in cargo, an independent surveyor or cargo specialist should be appointed.
2	Cargo sampling	In order to determine the average moisture content, the samples are taken from the full depth of the stockpile.
3	Cargo TML testing in suitable lab	In order to get reliable transportable moisture limit (TML) values, representative samples of the cargo have to be tested in laboratories.
4	Awareness of the risk of cargo liquefaction on-board ship	In case of unprocessed ore cargoes being transported, captain and officers should be aware of liquefaction.
5	Declaration of the average moisture content of the cargo before loading	The shipper has to present a declaration of the average moisture content of the cargo correctly before loading.
6	Cargo identification	The name of the cargo should be described by using the Bulk Cargo Shipping Name as detailed in the IMSBC Code.
7	Can test application	The can test, which is commonly used by Masters for approximately determining the possibility of flow on board a ship or at the port.
8	Procedures of IMSBC Code	The IMSBC Code procedures should always be followed when conducting transportable moisture limit tests
9	Understand of MSDS	A MSDS describes the properties and potential hazards of the cargo, how to carry it safely, and what to do in an emergency.
10	Stockpiles of cargo at port before loading	Different stockpiles might have been stored under varying conditions. Different stockpiles should be evaluated separately
11	Water or other liquids ingress into holds during loading	The moisture content will increase in case of precipitation and high humidity during loading.
12	Weight distribution	The IMSBC Code requires that, distributing the weight evenly over the hold top.
13	Cargo trimming status	The cargoes should be trimmed as necessary to ensure that they are reasonably level.
14	Cargo control/monitoring during voyage	During voyage, the cargo in the holds should be monitored for excess water or other signs of liquefaction.
15	Time İnterval between sampling/testing and loading	The interval between testing for moisture content and loading the cargo must be as small as practicable (7 days).
16	Loading wet/humid cargo	Loading wet cargo increases the risk of solid bulk cargo liquefaction risk.
17	Loading cargo whose moisture content above TML	TML indicates the maximum moisture content of the cargo which is considered safe for carriage.
18	Moisture content in cargo	High moisture content in cargo increases the risk of capsizing due to solid bulk cargo liquefaction.
19	GM Value	An excessively low or negative GM value increases the risk of a ship capsizing.
No	**Safety Barriers**	**Definitions**
1	Pumping out hold bilges	Discharging of the liquid accumulated in bilge wells out of the ship.
2	Cargo hold monitoring/controlling	Monitoring the holds for excess water during voyage.
3	Ballast operation	Attempting to correct the deteriorated stability due to cargo liquefaction by ballasting / de-ballasting operation.

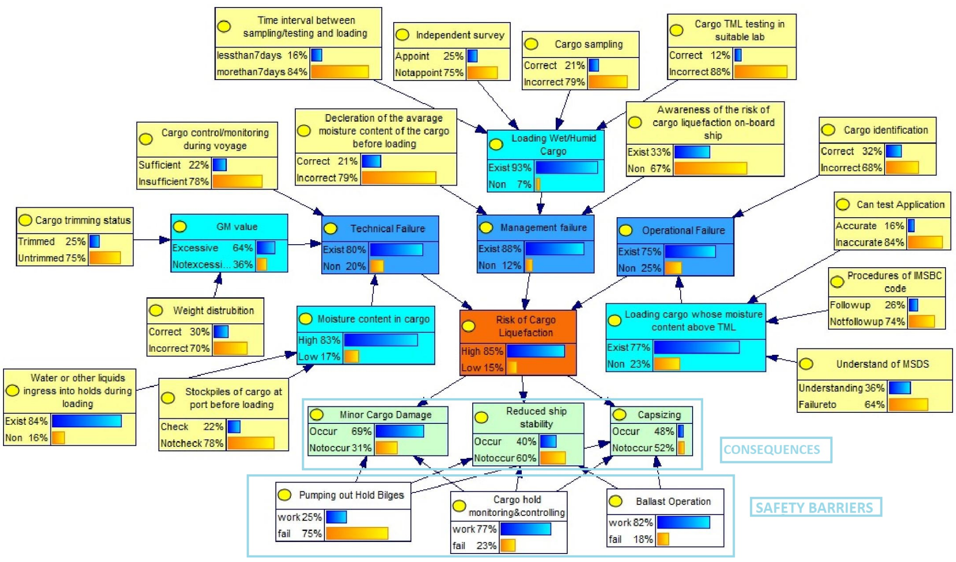

Figure 3. BN diagram for risk of solid bulk cargo liquefaction

Table 4. Linguistic expert evaluation and fuzzy possibility scores (FPs) of the root events

Root Events	Expert Judgments						Aggregation of Fuzzy Numbers				FPs
	1	**2**	**3**	**4**	**5**	**6**					
Independent survey	ML	L	ML	L	L	L	0,131	0,231	0,261	0,361	0,25
Cargo sampling	VL	ML	L	VL	ML	VL	0,095	0,149	0,235	0,335	0,21
Cargo TML testing in suitable lab	VL	L	L	VL	VL	VL	0,035	0,069	0,135	0,235	0,12
Awareness of the risk of cargo liquefaction on-board ship	L	ML	L	M	ML	ML	0,201	0,301	0,355	0,455	0,33
Declaration of the average moisture content of the cargo before loading	L	L	VL	VL	M	VL	0,116	0,172	0,216	0,316	0,21
Cargo identification	L	M	L	VL	M	ML	0,217	0,301	0,331	0,431	0,32
Can test Application	VL	VL	VL	ML	L	L	0,065	0,115	0,181	0,281	0,16
Procedures of IMSBC code	L	M	L	L	L	L	0,160	0,260	0,260	0,360	0,26
Understand of MSDS	M	ML	L	VL	M	M	0,252	0,336	0,372	0,472	0,36
Stockpiles of cargo at port before loading	L	L	L	ML	VL	ML	0,109	0,189	0,239	0,339	0,22
Water or other liquids ingress into holds during loading	H	H	H	VH	VH	H	0,736	0,836	0,872	0,936	0,84
Weight distribution	L	M	L	ML	L	ML	0,189	0,289	0,319	0,419	0,30
Cargo trimming status	ML	L	ML	L	L	L	0,131	0,231	0,261	0,361	0,25
Cargo control/monitoring during voyage	L	L	ML	L	L	L	0,115	0,215	0,229	0,329	0,22
Time interval between sampling/testing and loading	VL	L	L	VL	L	L	0,068	0,136	0,168	0,268	0,16

Table 5. Safety barrier assessment

Safety Barriers	Expert Judgments						Aggregation of Fuzzy Numbers				FPs
	1	2	3	4	5	6					
Pumping out hold bilges	ML	ML	L	L	VL	ML	0,129	0,209	0,279	0,379	0,25
Cargo hold monitoring/controlling	H	MH	M	H	VH	VH	0,649	0,749	0,803	0,869	0,77
Ballast operation	H	VH	H	MH	H	VH	0,701	0,801	0,851	0,917	0,18

Table 6. Conditional probability of loading wet/humid cargo

Independent survey	Appoint								Not appoint							
Cargo sampling	Correct				Incorrect				Correct				Incorrect			
Cargo TML testing in suitable lab	Correct		Incorrect		Correct		Incorrect		Correct		Incorrect		Correct		Incorrect	
Time interval between sampling /testing and loading	<7 days	> 7 days	<7 days	> 7 days	< 7 days	> 7 days	< 7 days	> 7 days	< 7 days	> 7 days	< 7 days	> 7 days	< 7 days	> 7 days	< 7 days	> 7 days
Exist	0.001	0.048	0.120	0.847	0.062	0.729	0.879	0.997	0.009	0.264	0.491	0.975	0.320	0.950	0.981	1.000
Non	0.999	0.952	0.880	0.153	0.938	0.271	0.121	0.003	0.991	0.736	0.509	0.025	0.680	0.050	0.019	0.000

3.2. Sensitivity analysis

The Bayesian network's sensitivity analysis can assist focus on the factors that can affect the target node the most while also verifying that the variables are ranked in significance for their impacts (Laskey, 1995). Some variables are chosen from various levels of the network structure in order to evaluate the extent of cargo liquefaction risk impacted by root nodes. The next step was to examine changes in the probabilities of the model's variables by increasing or decreasing their original probabilities (Kabir et al., 2015; Lampis and Andrews, 2009). Figure 4 shows the sensitivity analysis's outcome.

3.3. Validation

To confirm the reliability of model findings, validation is necessary. Three different axiom tests were applied to partially verify the suggested model in this study (Pristrom et al., 2016; Jones et al., 2010). The details of these tests are as follows:

Axiom 1: A specific increase or decrease in each parent node's prior probabilities should unquestionably cause a corresponding relative increase or decrease in the child nodes' posterior probabilities.

Axiom 2: The effect rates on the values of the child nodes and the rate of changes applied to the prior probability distributions of each parent node should be consistent.

Axiom 3: The aggregate impacts of the parent nodes on the child node are always anticipated to be bigger than the individual effects for a child node with multiple parent nodes.

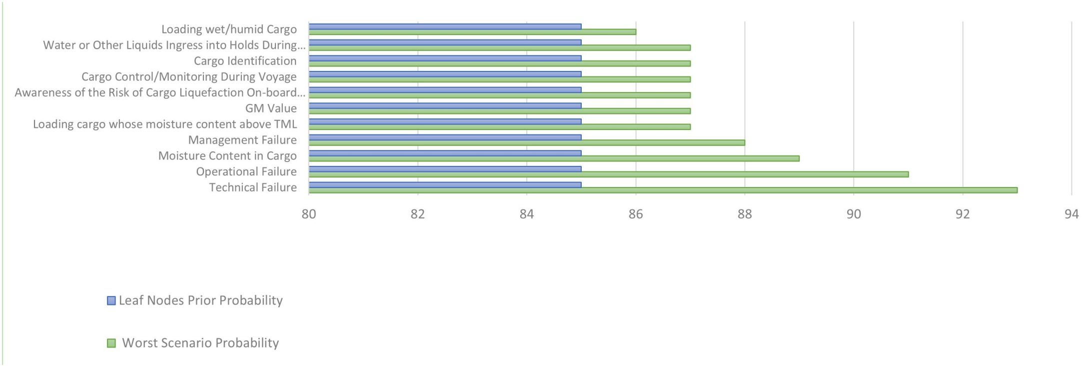

Figure 4. Sensitivity analysis for the BN

4. Findings and extended discussions

In this paper, a risk analysis for the consequences of solid bulk cargo liquefaction was performed under the Fuzzy Bayesian Network approach. In the view of the sensitivity analysis (figure 4), awareness of the risk of cargo liquefaction on-board ship, cargo control/monitoring during the voyage, cargo identification, and water or other liquids ingress into the hold during loading are the most important root causes which contribute to the risk of solid bulk cargo liquefaction

The findings of the sensitivity analysis also show that technical failure has a significant impact on cargo liquefaction risk. When the probability of occurrence of "technical failure" increases to 100%, the probability of cargo liquefaction occurring increases by 8%. Operational failure is another significant contributing intermediate event for solid bulk cargo liquefaction risk since the occurrence probability of solid bulk cargo liquefaction risk increases by 7%. In addition, axiom tests were performed for the risk of solid bulk cargo liquefaction to verify the results. As a result of axiom tests, technical failure (intermediate node) had the highest impact on cargo liquefaction risk. Likewise, operational failure had the second-highest impact on the risk of cargo liquefaction. Management failure is another important intermediate node that contributes to solid bulk cargo liquefaction. When the probability of management failure occurrence is increased to 100%, the risk of solid bulk cargo increases by 3%.

The consequences of cargo liquefaction are associated with safety barriers, which aim to mitigate damage. In case of cargo liquefaction, in high-risk situations without safety barriers, the probability of minor damage occurring, reduced ship stability, and capsizing is 99%. If safety barrier 1 (pumping out hold bilges) works and safety barrier 2 (cargo hold monitoring/controlling) works, the occurrence probability of minor damage decreased from 99% to 41%. Where the risk of cargo liquefaction is high is if barrier 1 works and barrier 2 fails. Then the occurrence probability of minor damage is 95%. If safety barrier 2 works and safety barrier 1 fails, probability of minor damage occurring is 84%.

If safety barriers 1, 2, and 3 (ballast operation) work, then the probability of reduced ship stability decreased from 99% to 5%. If only 1 and 2 of the safety barriers work and 3 fails, the probability of reduced ship stability decreased from 99% to 77%. If only 1 and 3 of the safety barriers work and 2 fails, the probability of reduced ship stability decreased from 99% to 42%. If only 2 and 3 of the safety barriers work and 1 fails, the probability of reduced ship stability decreased from 99% to 27%.

If safety barriers 1, 2, and 3 (ballast operation) work, then the occurrence probability of capsizing decreased from 99% to 21%. If only 1 and 2 of the safety barriers work and 3 fails, the probability of capsizing decreased from 99% to 80%. If only 1 and 3 of the safety barriers work and 2 fails, the probability of reduced ship stability decreased from 99% to 88%. If only 2 and 3 of the safety barriers work and 1 fails, the probability of reduced ship stability decreased from 99% to 38%.

In view of findings, it appears that safety barrier 2 is the most effective control action to minimize the capsizing consequences of solid bulk cargo liquefaction. To prevent the capsizing of the ship, cargo hold monitoring and controlling should be performed successfully during the voyage. Pumping out hold bilges is the most contributing factor for minor cargo damage and reduced ship stability consequences from solid bulk cargo liquefaction.

5. Conclusion

This paper aims to conduct a probabilistic risk analysis for solid bulk cargo liquefaction on-board ships since cargo liquefaction is a great hazard for bulk carrier ships due to the stability reduction. The stability of the ship can be reduced due to the free surface effect of cargo liquefaction and may result in capsizing. The topic, solid bulk cargo liquefaction due to the presence of excess moisture and the motions of the ship, has not been given the amount of attention it deserves in the maritime industry since the consequences of solid bulk cargo liquefaction may create life-threatening situations. Therefore, the Bayesian network and fuzzy logic methods were used for a detailed probabilistic risk analysis and carried out to find which can determine the conditional probability of each root and intermediate node of the solid bulk cargo handling operation.

The findings show that awareness of the risk of cargo liquefaction onboard ships, cargo control/monitoring during the voyage, cargo identification and water or other liquids ingress into hold during loading are focal points that may cause solid bulk cargo liquefaction. In the consequence analysis, safety barrier 2 (cargo hold monitoring/controlling) appears to be the most effective control action to avoid cargo liquefaction damage. Meanwhile, the findings of the paper were compared with a similar study where fuzzy bow-tie methodology was used (Akyuz et al., 2020). The fuzzy BN provides almost similar results to the fuzzy bow-tie approach if initial events/nodes are independent of each other. On the other hand, a scenario analysis provides updated an probability of the initial events/nodes to be given in the occurrence of cargo liquefaction precursors (Khakzad et al., 2011).

As a consequence, solid bulk cargo owners and shippers, maritime safety experts, and HSEQ managers (Health, Safety, Environment, and Quality) can benefit greatly from understanding the risks associated with solid bulk cargo liquefaction in the maritime industry. Perception awareness of risk of cargo liquefaction, cargo monitoring during the voyage, cargo identification, water, or other liquids not ingress into the hold during loading operation are paramount points to be considered by decision-makers before and during loading of solid bulk cargoes (such as nickel ore and iron ore) which may be liquefied.

Since there is lack of a detailed case study reports associated with solid bulk cargo liquefaction accidents, the paper applied the Bayesian Network method for assessing the probability of liquefaction for solid bulk cargoes without using a specific case study (a specific ship with a specific cargo that may be liquefied). A real-case application will be studied in future work once full-length accident reports will be available.

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