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Development of risk model for marine logistics support to offshore oil and gas operations in remote and harsh environments

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ABSTRACT

Logistics support to offshore operations is challenging, especially under severe environmental conditions such as those in the Arctic and sub-Arctic. The dominant environmental conditions, including waves, wind, poor visibility and the presence of icebergs and sea ice determine the mode and success of logistics support. Use of helicopters as a mode of logistics transport becomes ineffective when the distance is longer, the visibility is low, or the weather is stormy. Marine logistics support is more reliable and versatile. The present work focuses on developing a model for assessing risk associated with marine logistics operations in remote offshore locations (beyond helicopter reach) frequented with harsh environmental conditions (high winds, waves, and icy conditions). The key factors that affect such operations are identified and failure models are developed using fault trees. As an improvement, advance fault trees are adopted to relax the inherent limitations of the primary model. Uncertainties in both data and model are considered using the fuzzy inference system and evidence theory. Application of the proposed model is demonstrated through a case-study concerning a remote North Atlantic offshore operation. The contribution of this study is the identification of the key factors controlling the marine logistics operation and the development of a robust risk model that helps to analyze criticality of the contributing factors. The proposed model has the potential to help to develop innovative risk management strategies to support offshore operations.

1. Introduction

Operations in harsh environmental conditions are challenging and pose significant risks to people and infrastructures as well as to the environment. The Arctic and sub-Arctic regions are considered to have the harshest environmental conditions in the world, due to the presence of ice, extreme cold, high winds and unpredictable weather changes. Despite the challenging conditions, these regions contain proven reserves of hydrocarbons and mineral resources leading to increased interest of the oil and gas and the mining industries (Tellier, 2008). The exploration and development of natural resources in these regions present significant safety and integrity challenges, which are identified as the lack of detail in construction and operation standards, restricted operating conditions due to extreme weather including different ice features such as pack ice and icebergs, remoteness, human factors and knowledge and data scarcity (Khan et al., 2014). The stakeholders need an improved understanding of operational challenges to ensure safe operations in such conditions.

A recent drilling project conducted by Statoil Canada Ltd. (Statoil) in the Flemish Pass Basin is an example of distant offshore exploration in the harsh Arctic environment. The Basin is located approximately 480 km east of St. John's, Newfoundland and Labrador (Fig. 1). This is the furthest offshore that Statoil has developed a project, which adds to the cost and logistics challenges (Project Description Summary - Statoil Canada Ltd., 2016). Additional fuel requirements to cover the long distance from shore means less cargo capacity for vessels and helicopters. The long trip distance, poor visibility due to the prevalent occurrence of marine fog, particularly in summer and spring, and recurrent storms negatively affect the safety and effectiveness of using helicopters for logistics operations (Jan-Erik, 2014). Therefore, marine vessels become the only mode of transport in such conditions. However, the presence of icebergs (March to July) and sea ice (winter and spring) may hamper timely vessel transit. In addition, strong winds, snow and freezing rain raise difficulties for on-board vessel operations. A formal risk assessment of marine logistics operations is required to consider these additional threats so that vessels can perform routine supply as well as successful emergency response.

The objective of this work is to develop a methodology for assessing risk and to identify critical factors associated with marine logistics operations in remote and ice-covered regions. The innovations in this

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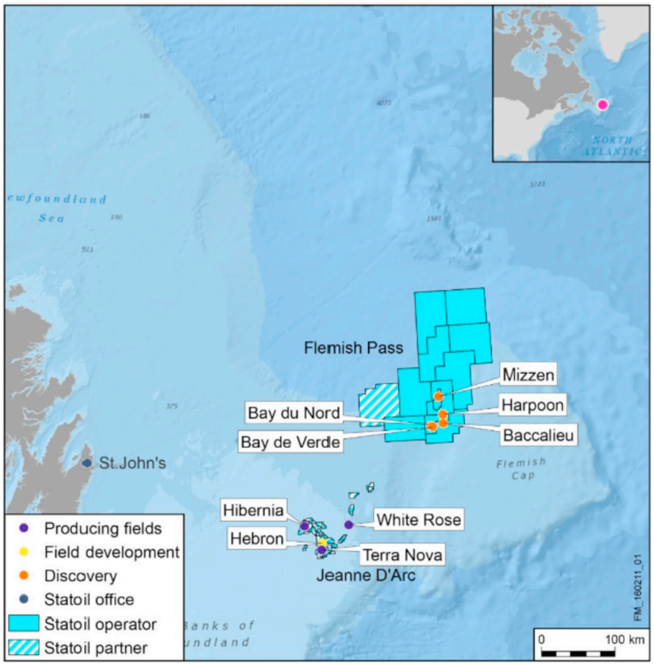

Fig. 1. Location of Statoil exploration drilling project in the Flemish Pass Basin. (Source: News/June 10, 2016/Statoil Canada Limited).

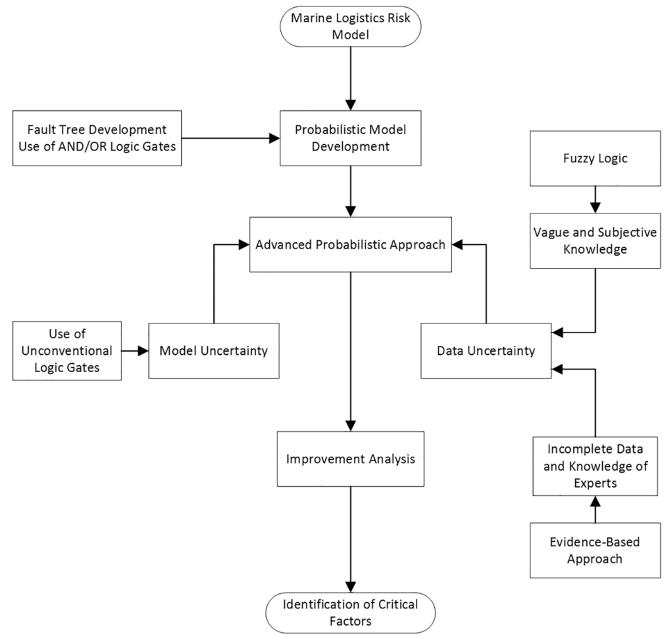

Fig. 2. The proposed framework for marine logistics support risk modelling in harsh environments.

work stem from: i) adapting an advance fault tree to overcome the assumption of independence of faults, ii) considering a fuzzy inference system to incorporate data uncertainty (vagueness and subjectivity), and iii) considering evidence theory to integrate data from multiple sources and incomplete data. The proposed unique model will help to analyze risk factors for marine logistics operations in quantitative terms. This will also help in developing effective and efficient risk management strategies.

The rest of this paper is organized as follows. Section 2 broadly describes the methodology for risk analysis of marine logistics operations and an illustrated example is presented in section 3. Section 4 discusses results and conclusions are provided in section 5.

2. Methodology to develop logistics risk model

The aim of this work is to develop a basis for assessing risk for logistics operations in harsh environments and to provide guidelines for safety measures to overcome associated challenges. The framework for this study is illustrated in Fig. 2. The possible factors that may affect the successful operation at each stage of a logistics operation are identified. A fault tree-based risk model is developed. This model is revised considering interdependence of parameters. The risk model is subsequently integrated with fuzzy and evidence theory to overcome the uncertainties of failure probability data. These steps are elaborated in the following sections.

2.1. Logical modelling of marine logistics support

2.1.1. Identification of main contributing factors

Logistics operations are conducted to transport personnel and to provide routine supplies as well as emergency support to recover from hazardous incidents. The sequence of activities involved in the process of an emergency logistics operation is presented in Fig. 3. This process consists of the following phases: departure readiness of a supply vessel when an incident has been reported, an uninterrupted voyage, functionality of on-board equipment, arrival at the site within the desired time limit and on-site operation. A successful logistics operation will not be possible if any of these phases fails. The risk factors that are involved in each phase of an operation are discussed in the following paragraphs.

2.1.1.1. Failure/delay due to departure readiness. The ship cannot depart for ER or logistics support if there is insufficient crew, a shortage of fuel for the distance, lack of safety equipment, or engine problems. Working in cold weather can endanger the crew unless proper preparations are made to equip the vessel and the crew for operating in the cold, dark, and icy conditions. Failure due to improper voyage plans has been addressed in detail by Kum and Sahin (2015). The vessel should be equipped with the following safety features for safe operation:

Lifesaving appliances: Lifeboats should be enclosed, and specially designed to operate in cold weather and turbulent water. Launching equipment should be designed to avoid the effects of freezing ice. Immersion suits are necessary for crew survival. The reliability information about lifesaving appliances is obtained from Bercha et al. (2003).

Firefighting equipment: Significant risks are associated with the use of firefighting equipment in extremely low temperatures, the most significant being the potential freezing of fluids in lines. Specific risks include:

- Freezing of firefighting equipment such as water hoses, piping, and nozzles.
- Portable fire extinguisher storage may be obstructed or frozen.
- Fire dampers may freeze in the stowage position.

Navigation equipment: Navigational equipment of a ship includes steering, hydraulic and propulsion systems. Faulty equipment may result in departure failure (Antao et al., 2006). A modern marine engine has a very complex structure that consists of many mechanical components as well as a fuel system, lubricating system, cooling system, auxiliary system and a control and safety system. The reliability features of a vessel engine were described in detail by Laskowski (2015) and Khorasani (2015).

2.1.1.2. Unobstructed voyage. The main factors that can disrupt the transit of a vessel are environmental factors (wind, waves and ice), loss

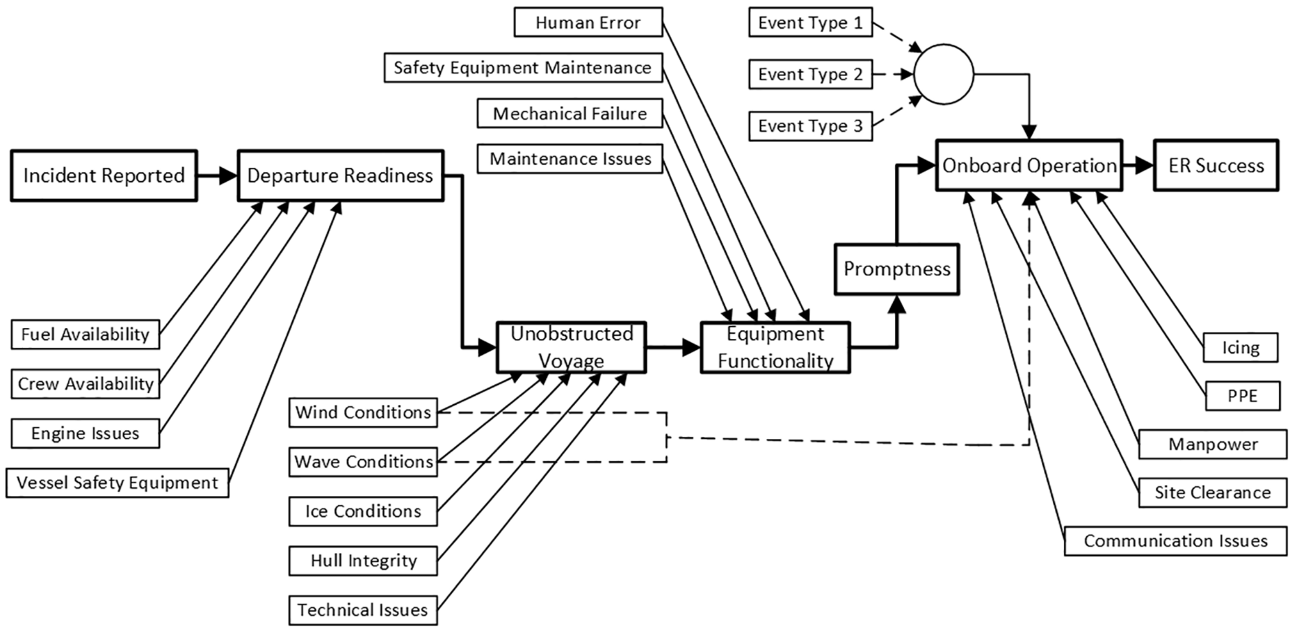

Fig. 3. Logistics operation or emergency response (ER) process.

of hull integrity and operational, navigational or communication failure.

Environmental factors: The northern regions have extreme climatic conditions that include prolonged winters with sub-zero temperatures, the presence of different forms of ice features and high wind and waves. Any precipitation in low temperatures results in snow, freezing rain or ice pellets that can reduce visibility and cause the accretion of ice on ships. Ice movement due to high wind and currents and presence of icebergs can impose the risk of ship besetting incidents. The reported ice conditions on ice charts or satellite imagery can change frequently, particularly the positions of the ice edge and the location of leads through the pack ice (ABS, 2010).

Loss of hull integrity: Ship hull integrity failure may lead to an unsuccessful operation. This failure can occur due to causes such as collision with an iceberg, human error or operational failure.

Navigational and operational Failure: Navigational failure may occur for many reasons that include radar failure, control error, propulsion system failure, human error, and difficulties arising from prevailing weather conditions such as poor visibility. Probabilistic assessment of a ship's navigational failure was presented by Pietrzykowski (2007); Amrozowicz et al. (1997). The operational safety features of vessels operating in polar waters have been described in IMO (2010). The presence of various forms of ice and harsh climatic conditions impose additional operational risk to vessels operating in the Arctic and sub-Arctic regions. Navigational and operational failure probabilities were presented in Afenyo et al. (2017).

2.1.1.3. Equipment functionality failure. The equipment may not be fully functional during the ER operation because of mechanical failure, lack of maintenance or human error.

Human error: According to Senders and Moray (1991), human error is a result of observable behaviour originating from psychological processes on different levels. It is evaluated against some performance standards, initiated by an event in a situation where it is possible to act in appropriate alternative ways. Human errors include three aspects:

- Evaluation of human behaviour against a performance standard or criterion.
- An event which results the measurable performance is not achieved; e.g. the expected level is not met by the acting agent.
- A degree of volition such that the actor has the opportunity to act in a way that will not be considered erroneous.

2.1.1.4. Promptness. The response time is very important for a successful operation. A complete operation could be considered a failure if the vessel does not arrive on time.

2.1.1.5. On-board fire/emergency response failure. On-site weather conditions and humans also play important roles in this case. The on-board operation may fail due to lack of manpower, absence of personal protective equipment or obstruction of the hazard's location.

2.1.2. Probabilistic logistics risk model

A fault tree (FT) is a quantitative risk analysis tool; a system or component failure is graphically presented as logical relationships with possible causes that can contribute to the system or component failure (Andrews and Moss, 2002). A system failure is referred to as a "top event" and all primary causes are defined as basic events, which are connected by logic gates in the FT. Basic events have binary states, i.e., success/failure, and are considered as mutually independent (Khakzad et al., 2011). There are several logic gates; however, the AND-gate and OR-gate are mostly used in the FT. A fault tree is adapted to its top event that includes only the most credible faults as assessed by the analyst and may not represent all possible system failure causes (Vesely et al., 1981).

The emergency response process has been defined and the contributing factors are identified in the previous sections; a simple FT model is developed and presented in parts from Figs. 4–7. The top event is emergency response (ER) failure, which is connected by an OR-gate with vessel readiness, unobstructed voyage, functionality of equipment, promptness and on-board operation, as failure of any of these events can cause top event failure. These intermediate events are further broken down to lower resolution events until primary causes are encountered. Promptness is considered as a basic event that has not been developed further in this study. Some of the basic events, e.g., human error or environmental causes, may affect different phases of the logistics operation, which have been considered in the FT model.

After constructing a fault tree, its outcomes can be analyzed both quantitatively and qualitatively. In quantitative analysis, the top event failure probability is calculated based on the failure probabilities of the

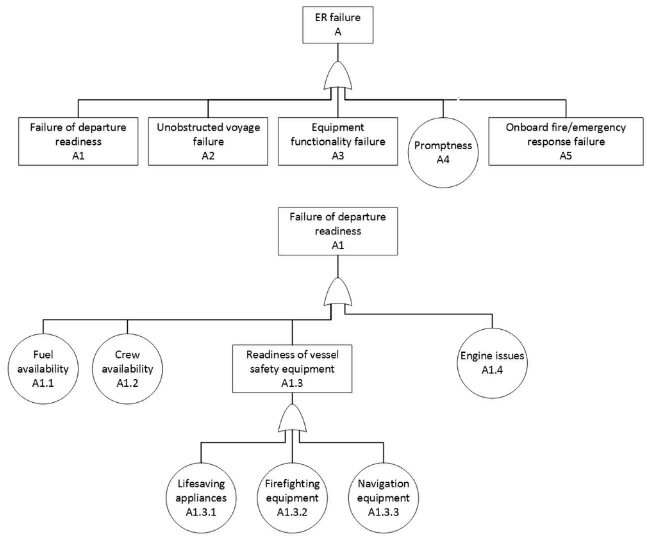

Fig. 4. Fault Tree model for logistics support to an offshore facility in remote harsh environment.

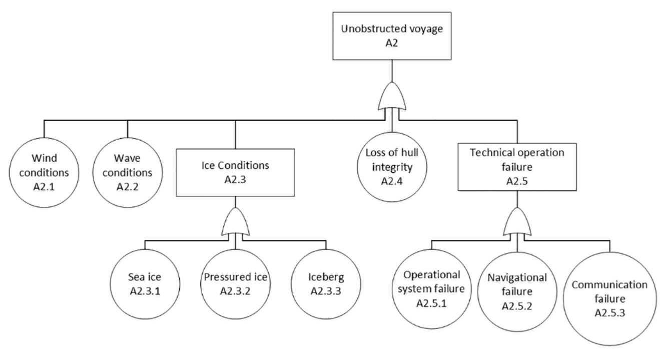

Fig. 5. Fault Tree model for unobstructed voyage failure.

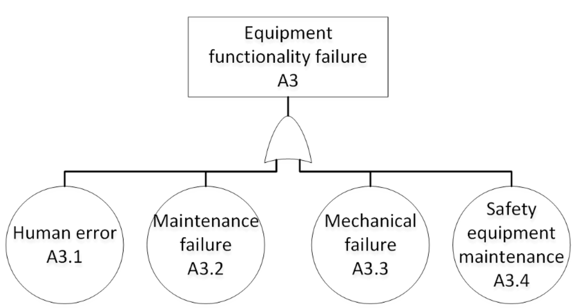

Fig. 6. Fault Tree model for equipment functionality failure.

basic events using Boolean algebra (Crowl and Louvar, 2002). Quantitative results are used for identifying quantitative rankings of contributions to system failure and the evaluation of model and data sensitivity (Vesely et al., 1981). In this study, the top event probability is calculated using quantitative analysis and the results are verified with the analysis conducted by the "Fault Tree +" software (Ferdous et al., 2007). The sensitivity analysis is performed to identify the critical factors and is presented in section 4. In qualitative analysis, minimal cut sets (MCS) are used for identifying the critical events to guide the best possible ways of risk reduction measures associated with the top event. A minimal cut set is a set of a minimum number of primary events that produces the top event if and only if all the events of the set occur. Since all the basic events in the primary FT model are connected by an OR-gate, failure of any basic event can lead to the top event failure, which means the total number of MCS will be equal to the number of basic events. Therefore, similar results can be obtained through the MCS approach and are not presented here.

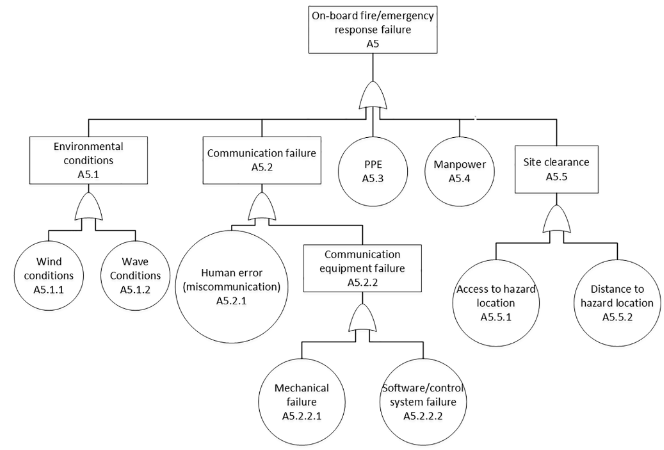

Fig. 7. Fault Tree model for on-site operational failure.

2.2. Adaption of advanced probabilistic approach to develop risk model

Although fault tree analysis (FTA) is a useful risk assessment technique, it suffers from some limitations such as the assumptions of mutually independent basic events and exclusively binary states of events. In addition, the traditional FTA cannot incorporate uncertainties in data. Several studies presented the fuzzy set theory (Mamood et al., 2013; Lavasani et al., 2011; Ferdous et al., 2009; Pan and Yun, 1997; Tanaka et al., 1983), the evidence theory (Ferdous et al., 2011; Limbourg et al., 2007), and the hybrid FTA (Lin and Wang, 1997) to deal with data uncertainty in FTA. In this study, the two main categories of uncertainty, namely, model uncertainty and data uncertainty, are considered.

The FT model is constructed based on several assumptions, which are summarized in Table 1. The identified approaches that can be adapted to relax the assumptions are: (1) use of the Inhibit gate to overcome independencies, and leaky AND/OR, noisy-OR/AND logic to overcome the binary nature and (2) use of a bayesian network (BN) – that provides the flexibility of interdependence and addresses model/data uncertainty. In this paper, a case study has been presented to show how the simplified OR-gate is replaced by the Inhibit gate in the FT to address dependencies.

Initially, environmental conditions such as wind, wave and ice conditions are assumed to be independent. However, incidents of sea ice and pack pressured ice occur when sea ice fields converge due to local wind, wave, and current conditions, as well as boundary conditions imposed by the local coastline geometry in near shore cases. These events can have serious implications for marine transport operations in ice-prone environments, as the ice fields impose extreme loads on vessels and structures, disrupt maneuverability and endanger personnel safety. Therefore, the combined effects of wind, wave and ice conditions should be considered in the study rather than treating those as separate independent events. Inhibit gates have been introduced to represent their dependencies. This study represents a scenario in which the ice conditions are dependent on the additional conditional events, wind and wave conditions. More details about the Inhibit gate are described by Andrews and Moss (2002). The modified FT has been presented in Figs. 8–10.

2.3. Data uncertainty

Table 2 summarizes the data related assumptions that may result in uncertainty in risk assessment. In the advance FTA, a fuzzy-based

Table 1
Model assumptions in the traditional FT model and approaches to relax the assumptions.

	Model Assumptions	Approach to Relax Assumptions	Reference
1	Traditional FT is static in nature and does not handle uncertainty. It does not offer the incorporation of newly available probability information into the model.	Bayesian network (BN) approach can offer probability updating in the analysis.	Khakzad et al. (2011)
2	It is assumed that all primary or basic events are independent.	Dependencies among primary events can be address by advanced logic gates e.g. Inhibit gate, or BN approach.	Andrews and Moss (2002)
3	Simplified OR-gates are used, which means that failure of any primary event will lead to a complete ER or logistics operation failure. Under this assumption, the failure probability estimation would be very conservative.	Inhibit gate or Noisy-OR gate may be considered to relax this conservative assumption.	Andrews and Moss (2002) Jensen and Nielsen (2007)
4	All events are assumed to possess a binary state (success/failure or working/not working).	Probabilistic gates such as noisy gate and gate with leak can be introduced that give the flexibility to choose an intermediate state of an event between 1 and 0 unlike AND/OR gates. In this way, the estimation of top event probability can be optimized.	Bobbio et al. (2001) Abimbola, M.O., PhD thesis (2016)
5	Environmental conditions such as wind, wave, or ice conditions are assumed to be independent and not region and time specific. In reality, these are significantly related. The dynamics of sea ice is governed by several driving forces such as wind, waves, internal ice stress divergence, Coriolis force, and sea surface tilt.	Inhibit gates may be considered in the FT model to address dependencies or conditional dependencies. Site specific and seasonal probability data should be used if available.	Coon et al. (1974) Sayed et al. (2002)
6	Intermediate events (A1 – A5) are placed in series to represent the process. It is assumed that the failure of any of these events will cause ER failure.	These events could be non-sequential and may have complex interdependencies. For example, dysfunctionality of marine equipment may happen at any stage of this operation which could affect timely departure of the vessel, unobstructed voyage and onboard operation. It may need a different approach and technique such as BN to develop the model, which is out of scope of the present study.	
7	Promptness (A4): the response time is a very important factor for the success of logistics operations. A complete operation could be considered a failure if the vessel is unable to arrive on time. In the FT model, this event is considered as two states: success or failure. However, the model should be developed so that it can be expressed in time, which will determine if the operation is either a failure or success.	BN model with multistate variables for response time during logistics operation can be developed to address this issue. Moreover, response time is dependent on vessel specifications, distance to the production facility, regional weather conditions etc. These factors are not considered in the existing model. At this moment, it is considered as an undeveloped event as more detail analysis is required with the support of relevant data and suitable approach.	Sarshar et al. (2013)
8	Loss of hull integrity (A2.4) is considered as an independent primary event, which in fact depends on many factors such as environmental (wind, waves, current, ice), operational failure etc.	Conditional dependencies among these factors can be introduced using BN approach.	
9	Crew availability (A1.2) has two states: yes/no.	It should be defined by two features: (a) adequate numbers of crew and (b) whether they are trained/qualified for the operation.	
10	There are many factors that may lead to engine issues (A1.4). However, the details are not considered in this study.	Engine failure may occur due to several reasons and the corresponding data of engine failures is not currently available. This assumption can be relaxed when more internal details of design and operational characteristics of marine engines become available.	
11	The FT model has the limitation of integrating subjective and imprecise events such as human error in failure logic model.	Fuzzy-based FTA or evidence-based FTA approach can be adopted for overcoming these limitations.	Mahmood et al. (2013) Lin and Wang (1997) Ferdous et al. (2009)
12	During on-board operation, it is assumed that all personnel are fit and equally skilled to conduct the operation.	Defined personnel states can be characterised in the model using BN.	

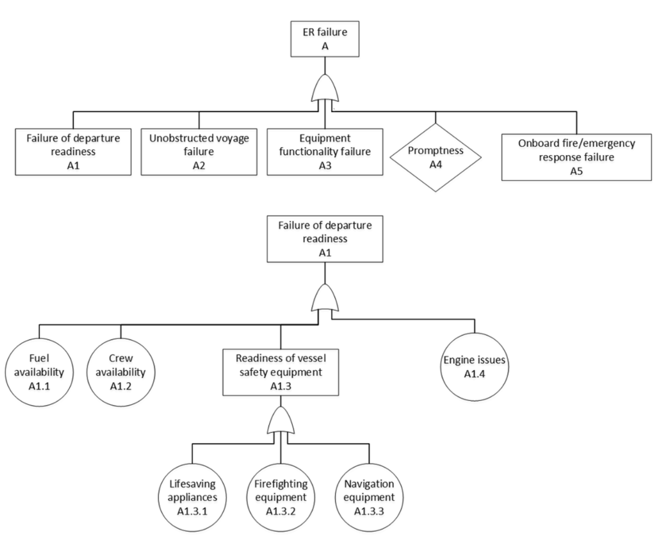

Fig. 8. Modified Fault Tree model for marine logistics support in remote harsh environment.

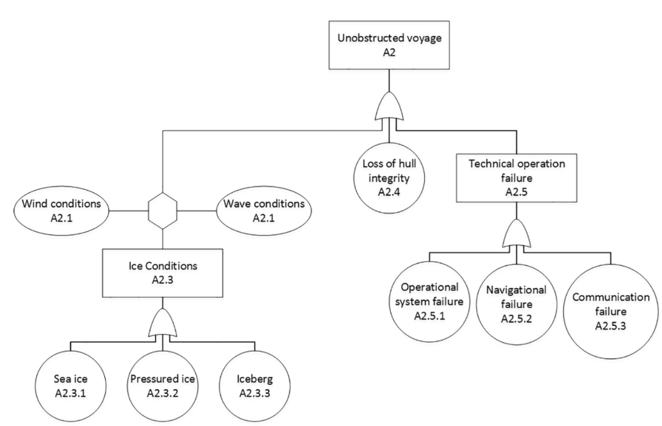

Fig. 9. Modified Fault Tree model for unobstructed voyage failure.

approach is adopted to the address vagueness and subjectivity of failure probability data, and evidence theory is applied to address incomplete and missing data as well as incorporating different experts' opinion in the analysis.

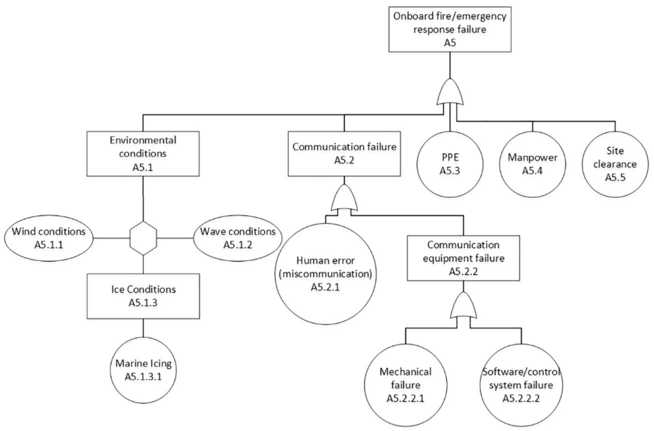

Fig. 10. Modified Fault Tree model for onsite operational failure.

2.3.1. Vagueness and subjectivity of data

The theory of Fuzzy sets was first introduced by Zadeh (1965). It provides a unique way to address vagueness and data uncertainty. In traditional FTA, system failure is evaluated based on the exact value of failure probabilities of the basic events. However, it is difficult to estimate a precise failure rate or the probability of components failure due to lack of sufficient data or the vague character of the events (Mahmood et al., 2013). Fuzzy-based approaches effectively deal with imprecision that arises due to subjectivity/vagueness, which can be useful in risk assessment to handle these types of uncertainties (Ferdous et al., 2009).

The fuzzy set of an event contains fuzzy numbers that have varying degrees of membership function (μ) ranging from 0 to 1. The relationship between the event probability and a membership function is represented by a fuzzy set. The degree of membership of element x in the fuzzy set of an event p is mathematically represented as (Ross, 2004):

$$\mu_p(x) \in [0, 1]$$

Fuzzy numbers can be of any form; however, triangular or trapezoidal fuzzy numbers are commonly used in reliability and risk assessments. A triangular fuzzy number (TFN) is used in this study, where fuzzy intervals are determined by different α- cut values. Fig. 11 illustrates a TFN and the fuzzy intervals are obtained using the following equation (Ferdous et al., 2011; Pan and Yun, 1997):

$$p_\alpha = [p_l + \alpha(p_m - p_l),\ p_u - \alpha(p_u - p_m)] \tag{1}$$

where p_l, p_m, and p_u represent minimum, most likely, and upper values, respectively, in the α- cut level.

The fuzzy-based FTA involves the following steps: (1) Generation of fuzzy probabilities of basic events TFN at various α- cut levels, (2) Estimation of fuzzified top event failure probabilities based on Tables 3, and (3) Defuzzification of top event failure probability to a crisp value.

There are several methods for the defuzzification process, such as the centre of area method, centre of maxima method, mean of maxima method, and weighted average defuzzify method. For this problem, top event fuzzy failure probability sets are defuzzified using the centre of maxima method (Klir and Yuan, 1995).

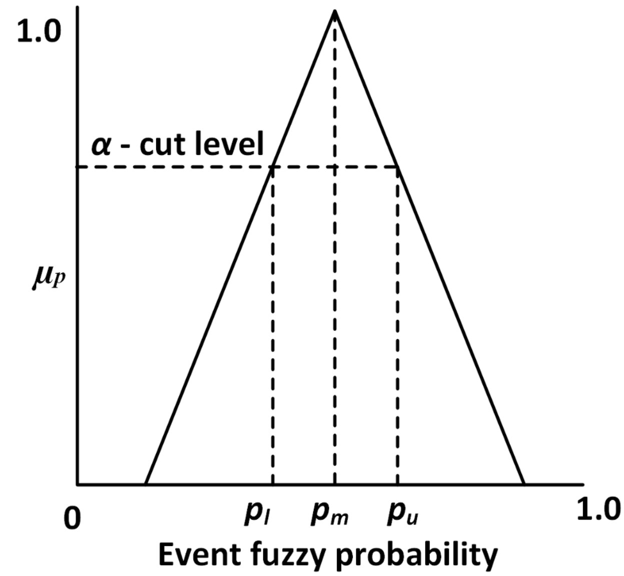

Fig. 11. Representation of triangular fuzzy number of an event.

Table 3
Arithmetic expressions for fuzzy FTA.

Gate type	α- cut formulation
OR-gate	$p_l^\alpha = 1 - \prod_{i=1}^{n}(1 - p_{il}^\alpha)$; $p_u^\alpha = 1 - \prod_{i=1}^{n}(1 - p_{iu}^\alpha)$
AND-gate	$p_l^\alpha = \prod_{i=1}^{n} p_{il}^\alpha$; $p_u^\alpha = \prod_{i=1}^{n} p_{iu}^\alpha$

2.3.2. Incomplete data and conflict between expert opinion

Evidence theory was first proposed by Dempster (1966) and later extended by Shafer (1976), which is also known as the Dempster-Shafer Theory (DST). Missing data and conflicting subjective data can be addressed by evidence theory. This helps in many ways, such as integrating data from different sources, filling missing data sources, resolving the issue of varying data for the same cause/event, and updating the probability when new information becomes available.

According to DST, an event probability is defined with a set of lower and upper bound values, which are denoted as belief and plausibility, respectively, and a mass is assigned for the uncertainty or ignorance about that event. DST application on the FTA was elaborately described by Ferdous et al. (2009 & 2011). The following steps are involved in evidence-based FTA:

(1) Defining the frame of discernment (FOD). In this study, FOD $\Omega = \{F, S\}$, where F and S indicate failure and success, respectively. The power set includes four subsets: $\{\Phi, \{F\}, \{S\}, \{F, S\}\}$ and cardinality; $|\Omega|$ is two.
(2) Assigning basic probability and ignorance of each basic event based on literature and expert opinions.

Table 2
Data assumptions in marine logistics risk analysis.

	Data Assumptions	Approach to Relax Assumptions	Reference
1	The failure probability data used in this study is for a specific period time.	Fuzzy theory can be employed to address this type of data limitation.	
2	For some events such as site clearance, PPE etc., historical failure rate data are not available. Hence, failure rate is assumed based on expert opinion.	Evidence theory can be introduced to deal with this issue. In addition, this approach enables the integration of different expert opinions. BN approach gives the flexibility to use data elicitation from experts.	Lavasani et al. (2011) Ferdous et al. (2011)

Table 4
Failure probabilities of basic events.

Intermediate Event	Basic Event	Probability of Failure	Reference
Failure of departure readiness (A1)	Fuel availability (A1.1)	3.97×10^{-4}	Kum and Sahin (2015)
	Crew availability (A1.2)	3.97×10^{-4}	Kum and Sahin (2015)
	Lifesaving appliances (A1.3.1)	1.00×10^{-3}	Bercha et al. (2003)
	Firefighting equipment (A1.3.2)	3.97×10^{-4}	Kum and Sahin (2015)
	Navigation equipment (A1.3.3)	2.55×10^{-3}	Antao et al. (2006)
	Engine issues (A1.4)	2.6×10^{-4}	Kum and Sahin (2015)
Failure of unobstructed voyage (A2)	Wind conditions (A2.1)	6.00×10^{-3}	Afenyo et al. (2017)
	Wave conditions (A2.2)	1.97×10^{-4}	Kose et al. (1997)
	Sea ice (A2.3.1)	2.75×10^{-3}	Kum and Sahin (2015)
	Pressured ice (A2.3.2)	5.94×10^{-2}	Kum and Sahin (2015)
	Iceberg (A2.3.3)	1.00×10^{-2}	Afenyo et al. (2017)
	Loss of hull integrity (A2.4)	1.33×10^{-4}	Christou et al. (2012)
	Operational system failure (A2.5.1)	1.00×10^{-4}	Afenyo et al. (2017)
	Navigational failure (A2.5.2)	2.00×10^{-6}	Afenyo et al. (2017)
	Communication failure (A2.5.3)	5.50×10^{-4}	Afenyo et al. (2017)
Equipment functionality failure (A3)	Human error (A3.1)	3.00×10^{-4}	Afenyo et al. (2017)
	Maintenance failure (A3.2)	1.00×10^{-4}	Expert opinion
	Mechanical failure (A3.3)	1.00×10^{-5}	Afenyo et al. (2017)
	Safety equipment maintenance (A3.4)	1.00×10^{-3}	Expert opinion
Promptness (A4)	Promptness (A4)	–	Undeveloped
On-board fire/emergency response failure (A5)	Wind conditions (A5.1.1)	6.00×10^{-3}	Afenyo et al. (2017)
	Wave conditions (A5.1.2)	1.97×10^{-4}	Kose et al. (1997)
	Marine icing (A5.1.3)	1.50×10^{-4}	Expert opinion
	Human error (miscommunication) (A5.2.1)	1.00×10^{-4}	Afenyo et al. (2017)
	Mechanical failure (A5.2.2.1)	5.46×10^{-2}	Bercha et al. (2003)
	Software/control system failure (A5.2.2.2)	4.00×10^{-4}	Afenyo et al. (2017)
	PPE (A5.3)	5.00×10^{-3}	Expert opinion
	Manpower (A5.4)	1.00×10^{-2}	Expert opinion
	Site Clearance (A5.5)	1.00×10^{-3}	Expert opinion

(3) Combining the individual beliefs of experts if there are more than one and generating a joint belief structure.
(4) Estimating belief and bet of the basic events and the top events.

3. Application of the proposed model

In this study, the failure probabilities of each basic event are obtained either from the literature or from expert opinions. The failure probabilities of the basic events and corresponding data sources are provided in Table 4.

The top event failure probability is estimated for both the traditional and advanced fault tree models and presented in Table 10. The failure probability calculated by traditional FTA is 0.1534, which can be interpreted as indicating that the chance of emergency response (ER) failure is about 1 in every 7 operations. This seems very conservative. In contrast, the estimated failure probability decreases to nearly half, which means the chance of failure becomes 1 in every 13 operations when the Inhibit gates are used. An Inhibit gate logically represents an AND-gate with an external conditional event. Therefore, the replacement of OR-gates with Inhibit gates considerably reduces the top event failure probability. Probability data related to the exact type of scenarios are not publicly available. However, based on Lloyd's worldwide data for 1994-97, the failure rate of cargo ships is 3.1×10^{-4} each year, which gives the probability of failure as 1 in 18 voyages, assuming two days per voyage (IAEA International Atomic Energy Agency (IAEA) report, 2001).

3.1. Application of fuzzy theory

In this study, a triangular fuzzy approach is adopted, where failure probabilities collected from the literature are considered as the most likely values of basic events. Reasonable lower and upper boundaries have been set to form the fuzzy triangle for each event. The projected failure probabilities of basic events are obtained from the corresponding fuzzy triangles for different α - cut levels. An example is provided in Table 5, where the confidence interval is chosen as 95% ($\alpha = 0.95$).

Fuzzified top event failure probabilities are estimated for each confidence interval and then defuzzified to crisp probability using the centre of maxima method. A comparison of the results is presented in Table 6.

3.2. Application of evidence theory

Evidence theory is used to consider incomplete data and integration of data from multiple sources. To illustrate the application of the theory to the proposed model, data from two different experts are used. Both experts have doctoral degrees, have conducted several offshore safety related projects and have more than five years of experience in the relevant area. The data from these two experts are provided in Table 7.

Two different sets of data have been used to formulate evidence theory in the FTA, which are combined using both DST and Yager rules. The combination rules are described in Ferdous et al. (2011); Smarandache and Dezert (2004); Yager (1987). A sample calculation is presented in Table 8.

Three important characteristics, namely, belief, plausible value and Bet of the top event are calculated and presented in Table 9.

4. Discussion

The failure probability of logistics operations is estimated using traditional FTA, advanced fuzzy-based FTA and evidence-theory-based FTA. The summary of results is provided in Table 10.

The traditional FTA gives significantly higher failure probability, as the construction of the FT model is overly simplified with OR-gates only, where factor dependencies and data uncertainties are not considered. In the advanced FTA, a non-traditional gate such as the Inhibit gate is introduced, which provides a less conservative probability estimate. The use of fuzzy theory in the advanced FTA offers a better decision-making approach when there is imitated data. The estimated

Table 5
Triangular Fuzzy Number at α = 0.95.

Basic Event	Probability of Failure/Fuzzy Number ("around")	Triangular Fuzzy Number (TFN)			95% Confidence (α = 0.95)	
		Minimum Value (P_l)	Most Likely Value (P_m)	Maximum Value (P_u)	Minimum Value (P_l)	Maximum Value (P_u)
Fuel availability (A1.1)	3.97E-04	1.99E-04	3.97E-04	7.94E-04	3.87E-04	4.17E-04
Crew availability (A1.2)	3.97E-04	1.99E-04	3.97E-04	7.94E-04	3.87E-04	4.17E-04
Lifesaving appliances (A1.3.1)	1.00E-03	5.00E-04	1.00E-03	2.00E-03	9.75E-04	1.05E-03
Firefighting equipment (A1.3.2)	3.97E-04	1.99E-04	3.97E-04	7.94E-04	3.87E-04	4.17E-04
Navigation equipment (A1.3.3)	2.55E-03	1.28E-03	2.55E-03	5.10E-03	2.49E-03	2.68E-03
Engine issues (A1.4)	2.60E-04	1.30E-04	2.60E-04	5.20E-04	2.54E-04	2.73E-04
Wind conditions (A2.1)	6.00E-03	3.00E-03	6.00E-03	1.20E-02	5.85E-03	6.30E-03
Wave conditions (A2.2)	1.97E-04	9.85E-05	1.97E-04	3.94E-04	1.92E-04	2.07E-04
Sea ice (A2.3.1)	2.75E-03	1.38E-03	2.75E-03	5.50E-03	2.68E-03	2.89E-03
Pressured ice (A2.3.2)	5.94E-02	2.97E-02	5.94E-02	1.19E-01	5.79E-02	6.24E-02
Iceberg (A2.3.3)	1.00E-02	5.00E-03	1.00E-02	2.00E-02	9.75E-03	1.05E-02
Loss of hull integrity (A2.4)	1.33E-04	6.65E-05	1.33E-04	2.66E-04	1.30E-04	1.40E-04
Operational system failure (A2.5.1)	1.00E-04	5.00E-05	1.00E-04	2.00E-04	9.75E-05	1.05E-04
Navigational failure (A2.5.2)	2.00E-06	1.00E-06	2.00E-06	4.00E-06	1.95E-06	2.10E-06
Communication failure (A2.5.3)	5.50E-04	2.75E-04	5.50E-04	1.10E-03	5.36E-04	5.78E-04
Human error (A3.1)	3.00E-04	1.50E-04	3.00E-04	6.00E-04	2.93E-04	3.15E-04
Maintenance failure (A3.2)	1.00E-04	5.00E-05	1.00E-04	2.00E-04	9.75E-05	1.05E-04
Mechanical failure (A3.3)	1.00E-05	5.00E-06	1.00E-05	2.00E-05	9.75E-06	1.05E-05
Safety equipment maintenance (A3.4)	1.00E-03	5.00E-04	1.00E-03	2.00E-03	9.75E-04	1.05E-03
Promptness (A4)	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
Wind conditions (A5.1.1)	6.00E-03	3.00E-03	6.00E-03	1.20E-02	5.85E-03	6.30E-03
Wave conditions (A5.1.2)	1.97E-04	9.85E-05	1.97E-04	3.94E-04	1.92E-04	2.07E-04
Marine icing (A5.1.3)	1.50E-04	7.50E-05	1.50E-04	3.00E-04	1.46E-04	1.58E-04
Human error (miscommunication) (A5.2.1)	1.00E-04	5.00E-05	1.00E-04	2.00E-04	9.75E-05	1.05E-04
Mechanical failure (A5.2.2.1)	5.46E-02	2.73E-02	5.46E-02	1.09E-01	5.32E-02	5.73E-02
Software/control system failure (A5.2.2.2)	4.00E-04	2.00E-04	4.00E-04	8.00E-04	3.90E-04	4.20E-04
PPE (A5.3)	5.00E-03	2.50E-03	5.00E-03	1.00E-02	4.88E-03	5.25E-03
Manpower (A5.4)	1.00E-02	5.00E-03	1.00E-02	2.00E-02	9.75E-03	1.05E-02
Site Clearance (A5.5)	1.00E-03	5.00E-04	1.00E-03	2.00E-03	9.75E-04	1.05E-03
Top Event Failure Probability					0.0749	0.0806

Table 6
Error robustness of fuzzy approach.

Considered Error in Data	Crisp Value	Deviation in Percentage
5%	0.0778	1.24
10%	0.0787	2.41
15%	0.0796	3.65
No Error	0.0768	0

failure probability using evidence theory seems relatively high. The outcome mainly depends on how the ignorance of probability data is set by different experts, based on the expert's knowledge. Also, evidence theory has the advantage that multi-source data can be integrated with the analysis and the model can be updated in the light of new information.

The analysis presented in this study demonstrated the effectiveness of the proposed framework to assess risk in logistics operations. It is therefore important to rank the critical factors, where preference should be given to improving the reliability of the operations. The improvement indices are used to identify the most critical basic events that lead to operational failure. The improvement index of an event is calculated by eliminating this event from the fault tree, to measure the reduction of the magnitude of top event failure probability (Ferdous et al., 2009; Tanaka et al., 1983; Misra and Weber, 1990). The following equation is used to evaluate this index:

$$F_{IM}(P_T, P_{Ti}) = (P_{il(T)} - P_{il(Ti)}) + (P_{iu(T)} - P_{iu(Ti)}) \quad (2)$$

where P_T and P_{Ti} refer to top event failure probability without and with an eliminated basic event, respectively. Subscripts l and u indicate the lower and upper bound of fuzzy numbers.

The high ratio of improvement indices and ER failure probability of the basic events are plotted in Fig. 12. This shows that mechanical failure, lack of skilled and experienced manpower, absence of suitable personal protective equipment, failure of navigation equipment and inadequate or missing lifesaving appliances are the most contributory factors that lead to ER failure. Mechanical failure includes a broad range of equipment failure during an on-board operation and the failure probability is significantly influenced by the weather conditions (Bercha, 2003). The correlations among mechanical failure, human error and existing environmental conditions are not considered in the FTA. Detailed investigation is required to improve the reliability assessment, which could be an area of future work.

5. Conclusions

This paper presents a risk model to analyze operational challenges of marine logistics support in harsh environmental conditions. The objective of this study is to identify the critical factors that will provide guidance to identify risk reduction measures to achieve a safer and faster approach in responding to this type of operation. For example, one such measure is the temporary offshore refuge, which needs to be further investigated. This work provides a basis for developing solutions to emergency marine logistics problems in remote and harsh regions.

Fault trees are used as a tool to develop the risk model. Application of the proposed FT model is demonstrated by studying an emergency response scenario. Although the fault tree is a common technique for assessing operational performance and reliability of a system, the traditional fault tree suffers from several limitations. Addressing interdependencies of events, adapting to new information and knowledge and handling uncertainties are of fundamental importance for a robust

Table 7
Basic probability assignments.

Basic Event	Expert 1			Expert 2		
	Failure {F}	Success {S}	{SF}	Failure {F}	Success {S}	{SF}
Fuel availability (A1.1)	3.61E-04	9.31E-01	0.069	4.37E-04	9.93E-01	0.0069
Crew availability (A1.2)	3.61E-04	9.31E-01	0.069	5.96E-04	9.93E-01	0.0069
Lifesaving appliances (A1.3.1)	9.09E-04	9.24E-01	0.075	1.50E-03	9.91E-01	0.0075
Firefighting equipment (A1.3.2)	3.61E-04	9.31E-01	0.069	5.96E-04	9.93E-01	0.0069
Navigation equipment (A1.3.3)	2.32E-03	9.28E-01	0.07	3.83E-03	9.89E-01	0.007
Engine issues (A1.4)	2.36E-04	9.30E-01	0.07	3.90E-04	9.93E-01	0.007
Wind conditions (A2.1)	5.45E-03	9.20E-01	0.075	9.00E-03	9.84E-01	0.0075
Wave conditions (A2.2)	1.79E-04	9.25E-01	0.075	2.96E-04	9.92E-01	0.0075
Sea ice (A2.3.1)	2.50E-03	9.23E-01	0.075	4.13E-03	9.88E-01	0.0075
Pressured ice (A2.3.2)	5.40E-02	8.71E-01	0.075	8.91E-02	9.03E-01	0.0075
Iceberg (A2.3.3)	9.09E-03	9.21E-01	0.07	1.50E-02	9.78E-01	0.007
Loss of hull integrity (A2.4)	1.21E-04	9.35E-01	0.065	2.00E-04	9.93E-01	0.0065
Operational system failure (A2.5.1)	9.09E-05	9.30E-01	0.07	1.50E-04	9.93E-01	0.007
Navigational failure (A2.5.2)	1.82E-06	9.32E-01	0.068	3.00E-06	9.93E-01	0.0068
Communication failure (A2.5.3)	5.00E-04	9.32E-01	0.068	8.25E-04	9.92E-01	0.0068
Human error (A3.1)	2.73E-04	9.25E-01	0.075	4.50E-04	9.92E-01	0.0075
Maintenance failure (A3.2)	9.09E-05	9.30E-01	0.07	1.50E-04	9.93E-01	0.007
Mechanical failure (A3.3)	9.09E-06	9.25E-01	0.075	1.50E-05	9.92E-01	0.0075
Safety equipment maintenance (A3.4)	9.09E-04	9.29E-01	0.07	1.50E-03	9.92E-01	0.007
Promptness (A4)	0.00E+00	9.30E-01	0.07	0.00E+00	9.93E-01	0.007
Wind conditions (A5.1.1)	5.45E-03	9.20E-01	0.075	9.00E-03	9.84E-01	0.0075
Wave conditions (A5.1.2)	1.79E-04	9.25E-01	0.075	2.96E-04	9.92E-01	0.0075
Marine icing (A5.1.3)	1.36E-04	9.25E-01	0.075	2.25E-04	9.92E-01	0.0075
Human error (miscommunication) (A5.2.1)	9.09E-05	9.25E-01	0.075	1.50E-04	9.92E-01	0.0075
Mechanical failure (A5.2.2.1)	4.96E-02	8.75E-01	0.075	8.19E-02	9.11E-01	0.0075
Software/control system failure (A5.2.2.2)	3.64E-04	9.30E-01	0.07	6.00E-04	9.92E-01	0.007
PPE (A5.3)	4.55E-03	9.30E-01	0.065	7.50E-03	9.86E-01	0.0065
Manpower (A5.4)	9.09E-03	9.23E-01	0.068	1.50E-02	9.78E-01	0.0068
Site Clearance (A5.5)	9.09E-04	9.34E-01	0.065	1.50E-03	9.92E-01	0.0065

Table 8
Combination of beliefs.

Fuel availability (A1.1)				
		F = Failure	S = Success	FS
		3.61E-04	3.61E-04	6.90E-02
F	4.37E-04	1.58E-07	1.58E-07	3.01E-05
S	9.93E-01	3.58E-04	3.58E-04	6.85E-02
FS	6.90E-03	2.49E-06	2.49E-06	4.76E-04
		k	3.58E-04	
		3.28E-05	6.89E-02	4.76E-04
DS		3.28E-05	6.89E-02	4.76E-04
Yager		3.28E-05	6.89E-02	8.35E-04
	Bel (F)	Pl (F)	Bel (S)	Pl (S)
DS	3.28E-05	5.09E-04	6.89E-02	6.94E-02
Yager	3.28E-05	8.67E-04	6.89E-02	6.97E-02

Table 9
Belief structures and "Bet" estimation of the top event.

Belief structures and "Bet"					
DS rule			Yager rule		
Bel	Pl	Bet	Bel	Pl	Bet
0.0203	0.1221	0.0712	0.0132	0.1814	0.0973

Table 10
Top event failure probability based on different approach.

Traditional FTA	Advanced FTA	Fuzzy-based FTA	Evidence-theory-based FTA	
		with 10% uncertainty	DS rule	Yager rule
0.1534	0.0768	0.0787	0.0712	0.0973

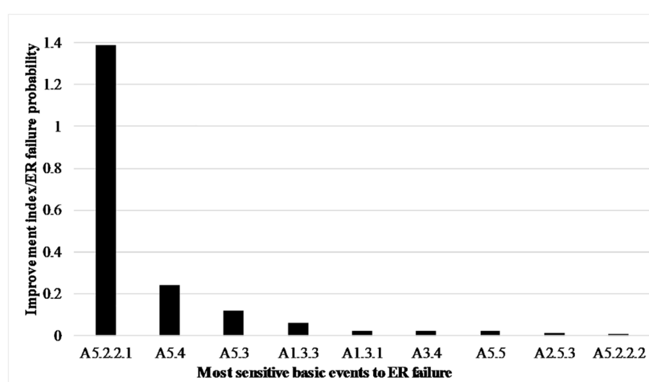

Fig. 12. Ratio of Improvement Index and ER failure probability of basic events (see Table 4 for legends).

risk model. This study addresses these points through:

(1) Consideration of interdependencies of events in the fault tree model through non-traditional gates such as the Inhibit gate.
(2) Consideration of data uncertainty in the earlier belief or data, which is important, as often, precise data for such analysis are not available. The fuzzy-based FTA approach helps to enhance robustness of the analysis in the presence of vague and subjective data.
(3) Consideration of missing data and conflicting subjective data using evidence theory. This consideration helps to integrate data from different sources, overcome a missing data problem, resolve the issue when there is varying data for the same event and update the probability.

The sensitivity analysis results reveal that the most critical phase of this process is conducting a successful on-board operation after reaching the target location. The main challenges include, but are not limited to, mechanical failure that comprises malfunction of lifeboats, failure to launch, inability to reach the installation due to severe ice conditions etc., and lack of trained and experienced personnel to conduct the operation in such harsh environmental conditions. The study presents a generic model, which may be used to conduct a marine logistics risk assessment and support an operation in a harsh offshore environment. The proposed model can be modified based on region-specific features and analysis should be performed using suitable probability data available for that region. Feedback from two experts with similar education and experience levels are considered in this study. More data from experts with diverse backgrounds such as academicians, ships' captains, and other offshore personnel can be incorporated when available. A weighting factor can be introduced based on the profession and experience of the experts. In addition, further investigation is required to develop "Promptness". Additional data and a different approach, i.e. a model that can define failure as a function of response time, can be proposed as future work. The use of the advance FTA is a useful tool to model risk for ER processes, although an alternative modelling approach, namely, the BN, has a more flexible structure than the fault tree and offers better representation of inter-dependencies and uncertainty handling capacity. Therefore, BN modelling of the ER operation could be a promising future study.

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References

Abimbola, M.O., 2016. Dynamic Safety Analysis of Managed Pressure Drilling Operations, PhD Thesis. Memorial University of Newfoundland.

Afenyo, M., Khan, F., Veitch, B., Yang, M., 2017. Arctic shipping accident scenario analysis using Bayesian Network approach. Ocean Eng. 133, 224–230. http://doi.org/10.1016/j.oceaneng.2017.02.002.

American Bureau of Shipping (ABS), 2010. Guide for Vessels Operating in Low Temperature Environments.

Amrozowicz, M., Brown, A.J., Golay, M., 1997. Probabilistic Analysis of Tanker Groundings. International Offshore and Polar Engineering Conference. Honolulu, Hawaii.

Andrews, J.D., Moss, T.R., 2002. Reliability and Risk Assessment. Wiley-Blackwell, Publisher.

Antao, P., Soares, C.G., 2006. Fault-tree models of accident scenarios of RoPax vessels. Int. J. Autom. Comput. 2, 107–116 2006.

Bercha, F.G., 2003. Escape, Evacuation, and Rescue Research Project Phase II.

Bercha, F.G., Brooks, C.J., Leafloor, F., 2003. Human Performance in Arctic Offshore Escape, Evacuation, and Rescue.

Bobbioa, A., Portinalea, L., Minichinob, M., Ciancamerlab, E., 2001. Improving the analysis of dependable systems by mapping fault trees into Bayesian networks. Reliab. Eng. Syst. Saf. 71, 249–260 2001.

Christou, M., Konstantinidou, M., 2012. Safety of Offshore Oil and Gas Operations: Lessons from Past Accident Analysis. JRC Scientific and Policy reports.

Coon, M.D., Maykut, G.A., Pritchard, R.S., Rothrock, D.A., Thorndike, A.S., 1974. Modeling the pack ice as an elastic-plastic material. AIDJEX Bull. 24, H05.

Crowl, D.A., Louvar, J.F., 2002. Chemical Process Safety: Fundamentals with Applications. Prentice Hall Publication Inc., pp. 601.

Dempster, A.P., 1966. New methods for reasoning towards posterior distributions based on sample data. Ann. Math. Stat. 37 (2), 355–374 1966.

Ercan Kose, E., Dincer, A.C., Durukanoglu, H.F., 1997. Risk assessment of fishing vessels. Tr. J. Eng. Environ. Sci. 22 (1998), 417–428.

Ferdous, R., Khan, F., Veitch, B., Amyotte, P.R., 2007. Methodology for Computer-Aided Fault Tree Analysis. https://doi.org/10.1205/psep06002.

Ferdous, R., Khan, F., Veitch, B., Amyotte, P.R., 2009. Methodology for computer aided fuzzy fault tree analysis. Process Saf. Environ. Protect. 87 (4), 217–226.

Ferdous, R., Khan, F., Sadiq, R., Amyotte, P.R., Veitch, B., 2011. Fault and event tree analyses for process systems risk analysis: uncertainty handling formulations. Risk Anal. 31, 1.

International Atomic Energy Agency (IAEA) report, July 2001. Severity, Probability and Risk of Accidents during Maritime Transport of Radioactive Material, Vienna. ISSN 1011–4289.

International Maritime Organization (IMO), 2010, MSC/Circ.1056–MEPC/Circ.399.

Jan-Erik, Vinnem, 2014. Offshore Risk Assessment vol 1. Principles, Modelling and Applications of QRA Studies.

https://www.statoil.com/en/news/efficient-exploration-offshore-newfoundland.html, June, 2016.

Jensen, F.V., Nielsen, T.D., 2007. Bayesian Networks and Decision Graphs. Springer, New York.

Khakzad, N., Khan, F., Amyotte, P., 2011. Safety analysis in process facilities: comparison of fault tree and Bayesian network approaches. J. Reliab. Eng. Syst. Saf. 96 (2011), 925–932.

Khan, F., Ahmed, S., Yang, M., Hashemi, S.J., Caines, S., Rathnayaka, S., Oldford, D., 2014. Safety challenges in harsh environments: lessons learned. Process Saf. Prog. 34, 191–195. https://doi.org/10.1002/prs.11704.

Khorasani, V.R., 2015. Risk Assessment of Diesel Engine Failure in a Dynamic Positioning System. Masters thesis, University of Stavanger, Norway.

Klir, G.J., Yuan, B., 1995. Fuzzy Sets and Fuzzy Logic: Theory and Applications, first ed. Prentice Hall PTR, Upper Saddle River, NJ.

Kum, S., Sahin, B., 2015. A root cause analysis for Arctic Marine accidents from 1993 to 2011. Saf. Sci. 74, 206–220.

Laskowski, R., 2015. Fault Tree Analysis as a tool for modelling the marine main engine reliability structure. Sci. J. Maritime Univ. Szczecin 41 (113), 71–77 2015.

Lavasani, M. R. Miri, Wang, J., Yang, Z., Finlay, J., 2011. Application of fuzzy fault tree analysis on oil and gas offshore pipelines. Int. J. Mar. Sci. Eng. 1 (1), 29–42.

Limbourg, P., Savic´, R., Petersen, J., Kochs, H.-D., 2008. Modelling uncertainty in fault tree analyses using evidence theory. Proc. Inst. Mech. Eng. O J. Risk Reliab. 222 (3), 291–302.

Lin, Ching-Torng, Wang, Mao-Jiun J., 1997. Hybrid fault tree analysis using fuzzy sets. Reliab. Eng. Syst. Saf. 58, 205–213 1997.

Mahmood, Y.A., Ahmadi, A., Verma, A.K., Srividya, A., Kumar, U., 2013. Fuzzy fault tree analysis: a review of concept and application. Int. J. Syst. Assur. Eng. Manag. 4 (1), 19–32 Jan-Mar 2013.

Misra, B.K., Weber, G.G., 1990. Use of fuzzy set theory for level-1 studies in probabilistic risk assessment. Fuzzy Sets Syst. 37, 139–160.

Pan, H., Yun, Y.W., 1997. Fault tree analysis with fuzzy gates. Comput. Ind. Eng. 33 (3–4), 569–572.

Pietrzykowski, Z., 2007. Assessment of navigational safety in vessel traffic in an open area. Int. J. Marine Nav. Saf. Sea Transport. 1 (1) March 2007.

Project Description Summary - Statoil Canada Ltd., 2016.

Ross, T., 2004. Fuzzy Logic with Engineering Applications, second ed. John Wiley & Sons, West Sussex, UK.

Sarshar, Parvaneh, Radianti, Jaziar, Granmo, Ole-Christoffer, Gonzalez, Jose J., 2013. A Bayesian Network Model for Evacuation Time Analysis during a Ship Fire. IEEE.

Sayed, M., Carrieres, T., Tran, H., Savage, S.B., 2002. Development of an operational ice dynamics model for the Canadian Ice Service. In: Proc. Int. Offshore and Polar Eng. Conf., ISOPE, Kitakyushu, Japan, May 26-31, pp. 841–848.

Senders, J.W., Moray, N.P., 1991. Human Error: Cause, Prediction, and Reduction. Lawrence Erlbaum Associates, Hillsdale, New Jersey.

Shafer, G., 1976. A Mathematical Theory of Evidence. Princeton University Press.

Smarandache, F., Dezert, J., 2004. Proportional conflict redistribution rules for information fusion. In: Applications and Advances of DSmT for Information Fusion, vol. 2. American Research Press, Rehoboth, MA, pp. 461.

Tanaka, H., Fan, T.L., Lai, F.S., Toughi, K., 1983. Fault tree analysis by fuzzy probability. IEEE Trans. Reliab. 32 (5), 455–457.

Tellier, Frédéric Beauregard, 2008. The Arctic: Hydrocarbon Resources. Parliament of Canada publication, PRB 08-07E.

Vesely, W.E., Goldberg, F.F., Roberts, N.H., Haasl, D.F., 1981. Fault Tree Handbook. U.S. Nuclear Regulatory Commission, Washington, DC.

Yager, R.R., 1987. On the Dempster-Shafer framework and new combination rules. Inf. Sci. 41 (2), 93–137.

Zadeh, L., 1965. "Fuzzy sets. Inf. Control 8, 338–353.