RISK MANAGEMENT OF OFFSHORE LOGISTICS SUPPORT OPERATIONS IN REMOTE HARSH ENVIRONMENTS

by

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To

my

parents

ABSTRACT

Activities in northern offshore regions are increasing due to proven reserves of natural resources. These regions are considered to have a harsh marine environment due to extreme weather conditions, namely low temperatures, frequent storms and the presence of sea ice. In general these activities are moving further offshore. Thus many new developments are faced with operations in extreme environments at long distances from shore support. Design, operational and regulatory planning for such offshore installations must consider the environmental challenges along with additional difficulties that arise due to remoteness.

The most significant aspects of an offshore development that are affected by the factors of environment and remoteness, are the logistical support functions required for daily operations and the rapid response required for emergencies. In the early stages of design it would be beneficial to have a means of assessing the high risk elements of such operations and the risk reduction cost effectiveness of proposed solutions.

This study presents an end-to-end risk reduction analysis of the logistical support functions for a typical remote harsh-environment offshore operation including; risk assessment to provide identification of most significant risks, risk reduction modeling and development of a solution to provide the identified most effective reduction strategy, and finally a cost benefit analysis that includes the costed initial risk factors, the solution cost and the costed net reduction in risk arising from implementation.

This research serves three functions. It develops a procedure for evaluating offshore operations that have inherently high logistical risks due mainly to distance but also applicable to other factors. It provides a risk analysis based solution to the specific problem of remote operations in harsh environments. Finally it develops a method of determining the utility of a possible solution or of alternative solutions through rational risk based cost analysis.

The study is divided into four phases, Risk Analysis, Risk Reduction, Specific Solution and Cost-Benefit Analysis. In phase one – risk analysis, an advanced probabilistic model is developed using fault trees to identify the main contributing factors of the logistical challenges. A fuzzy-based and evidence-based approach is implemented to address inherent data limitations. It is found that existing modes of logistics support such as marine vessel or helicopter are not sufficiently reliable and quick for remote offshore operations. Moving towards in phase two – risk reduction, a conditional dependence-based Bayesian model is developed that has integrated multiple alternative risk reduction measures. The analysis depicts that a nearby offshore refuge and an additional layer of safety inventory are found to the most effective measures. In phase three – specific solution, the concept of a moored vessel, which is termed as offshore resource centre (ORC) is proposed that can meet the functions of both these measures. The overall dimensions of the ORC are derived based on the functional requirements and the model is validated for stability and mooring requirements. In phase four – cost-benefit analysis, the life cycle costs of an ORC is estimated from historical vessel data using regression analysis. A loss model is developed for a hypothetical blowout incident, which is a function response time and the distance from shore support. These models are integrated into a single framework that can project the costed risk with or without the ORC. The analysis reveals that an ORC becomes more and more viable when the offshore distance becomes longer and if there is a higher probability of any platform incident, recognizing that it is desirable to keep the probability as low as possible. Taken together these phases form a full analysis from problem identification through solution cost-benefit.

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Nomenclature

BN	Bayesian network
CAT	Commercial air transport
DAG	Directed acyclic graph
DST	Dempster-Shafer theory.
ER	Emergency response
FT	Fault tree
FTA	Fault tree analysis
LCC	Life cycle cost
NPV	Net present value
ORC	Offshore resource centre
MCS	Minimal cut sets
TFN	Triangular fuzzy number
FOD	Frame of discernment
C-RISE	Centre for Risk, Integrity and Safety Engineering
CPT	Conditional probability table
HRA	Human reliability analysis
HEP	Human error probability
PSF	Performance shaping factor
MAIB	Marine Accident Investigation Branch
HSE	Health and Safety Executive
WOAD	Worldwide Offshore Accident Databank

ERV	Emergency response vessel
SBV	Standby vessel
ID	Influence diagrams
MOB	Mobile offshore base
DP	Dynamic positioning
FRC	Fast rescue craft
ILO	International Labor Organization
SOLAS	International Convention for Safety of Life
LF	Loss function
MCS	Monte Carlo Simulation
MLR	Multiple linear regression
CDF	Cumulative Density Function
BP	British Petroleum
AMSA	Australian Maritime Safety Authority

1. INTRODUCTION

1.1 Problem statement

Harsh offshore environments are characterized by extreme weather conditions, which are not favorable for human, infrastructure or habitat (Khan et al., 2014a). Northern ocean frontiers have the harshest environmental conditions with the presence of various ice features, extreme cold temperature, freezing rain, high wind and waves, and marine fog (Walsh, 2008; Arctic Marine Shipping Assessment, 2009; Hamilton, 2011; Meling, 2013; Necci et al., 2019). In addition, these regions, including the high Arctic, are most often also located at long distances from established large communities and infrastructure.

However, these regions contain proven and speculative reserves of hydrocarbons and mineral resources leading to increased interest from the oil and gas and mining industries (Tellier, 2008). Exploration and development of natural resources in these regions faces significant safety and integrity challenges, which are identified as the lack of details in construction and operation standards, restricted operating conditions, presence of different ice features such as pack ice and icebergs, remoteness, human factors, and knowledge and data scarcity (Khan et al., 2014b). There are several standards and practices such as ABS 2010, ISO 19906:2010, NORSOK S-002, and Barents 2020 that provide guidance for operations in harsh environments. However, there is a lack of design and operational guidelines or experience for further north, which must consider the additional distance and more extreme environmental conditions (Hamilton, 2011; Meling, 2013). Planning for normal logistics supply, and support during emergencies, is an important aspect of any resource development and a key part of regulatory evaluation. There is a need to be able to assess risk and develop new strategies and technologies prior to launching operations in these regions (Milaković et al., 2014; Malykhanov and Chernenko, 2015; Borch, 2018; Uthaug, 2018).

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 Figure 1.1. This process consists of the following phases: departure readiness of a 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 is unlikely if any of these phases fails.

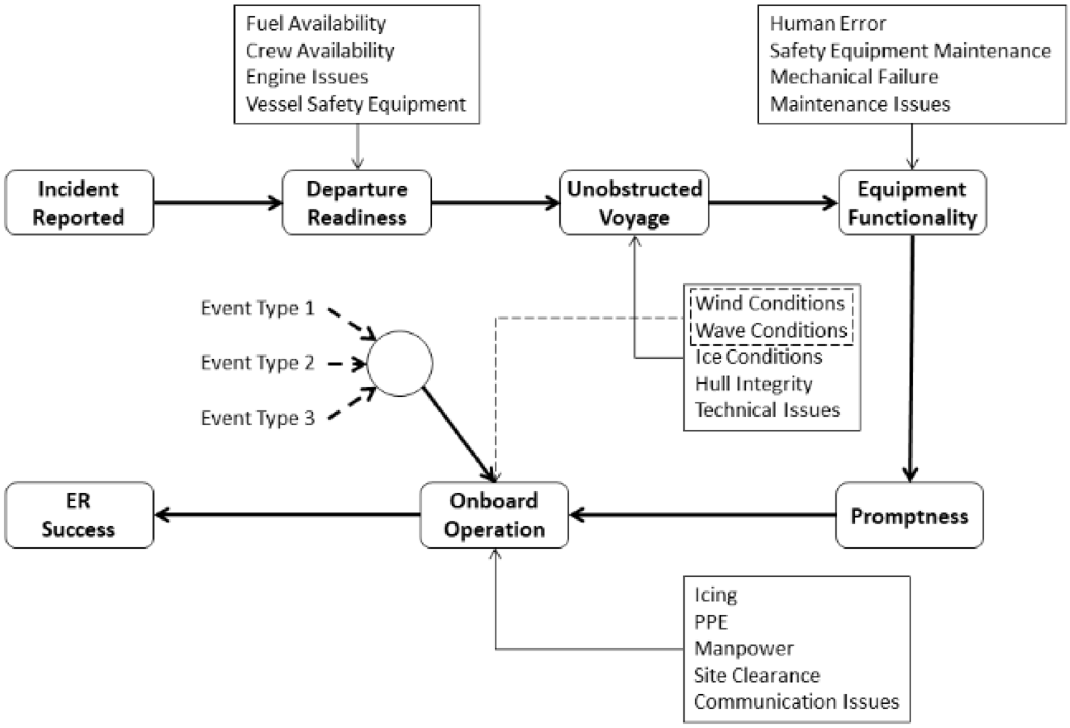

Figure 1.1: Logistics operation or emergency response (ER) process

1.2 Knowledge and technological gaps

Logistics for offshore operations is, in the majority of cases, provided by supply vessels and/or helicopters. In general, marine vessels are used for transporting materials and supplies from an onshore supply base to support offshore exploration activities. Helicopters are used to transport personnel and light cargo to and from offshore platforms. Besides the routine logistics for supply, the role of emergency response (ER) is to support emergency evacuation should the platform need to be abandoned. Prompt response, which can be critical due to the distance and environment, is required to enhance the resilience of an offshore system and minimize the severity of an accident.

Faster response can be provided by helicopter than by support vessel but the use of helicopter is limited when the distance is too long (beyond helicopter reach), and subject to adverse weather conditions. Also, helicopters cannot be used if the platform itself is sinking or any situation that is not safe for the helicopter to land or winch.

Accident rates in the offshore helicopter industry are still at least one order of magnitude greater than those of commercial fixed-wing operations (Oil & Gas UK, 2017; OGP, 2010). The crash of a helicopter is almost always a very serious event - often leading to fatalities and serious economic loss (Sutton, 2014; Okstad et al., 2012; Olsen and Lindøe, 2009; Hokstad et al., 2001; Vinnem, 2011, 2010). Baker et al. (2011) published an article on helicopter crashes related to oil and gas operations in the Gulf of Mexico, where an average of 6.6 crashes occurred per year during 1983 – 2009 and resulted in a total of 139 fatalities. During that period, bad weather led to a total of 29 crashes, which accounted to 40% of the 139 deaths. According to the Civil Aviation Authority and Oil & Gas UK records, there were 73 UK Continental Shelf offshore commercial air transport (CAT) accidents reported from 1976 to 2013 in which a total of 119 fatalities occurred. 11% of these accidents occurred due to external factors such as icing, turbulence, wind shear, thunderstorm, or bird strike. These problems are particularly acute at night, when the accident rates are considerably higher than those in the daytime. Knowledge of the hazards and risks associated with such accidents is very limited (Ross and Gibb, 2008). This is aggravated by the expected increase in nighttime or low light offshore helicopter activities associated with, for example, the beginning of exploration for oil and gas in polar regions (Nascimento, 2014). Marine vessels could become the only mode for transportation if these circumstances lead to unacceptably high risk. The feasibility of marine logistics operations in remote harsh environments is not well-understood (Khan et al., 2014a, 2014b). A marine logistics operation can be hampered by many factors, such as equipment failure, operational and navigational failure, failure due to the prevailing environment, human related error, etc. Logistics support failure due to inadequate voyage plans has been addressed in detail by Kum and Sahin (2015). Working in northern regions can endanger the crew unless proper preparations are made to equip both vessel and crew for operating in cold, dark, and icy conditions. The reliability information about lifesaving appliances in ice-covered regions is presented in Bercha et al. (2003). Faulty equipment in any system of a ship may result in operation failure (Antao et al., 2006). Navigational failure may occur for many reasons including radar failure, control error, propulsion system failure, human error, or difficulties arising from prevailing weather conditions such as poor visibility. Probabilistic assessment of a ship's navigational failure is presented by Pietrzykowski (2007) and Amrozowicz et al. (1997).

The term "risk" refers to the probability of an undesirable event and its consequence to people, property and environment. Various modelling techniques are available to assess the risk of a system qualitatively or quantitatively in which Fault Tree (FT) or Bayesian Networks (BN) are commonly used. However, choosing the right approach is key for useful risk assessment (Crowl and Louvar, 2002; Andrews and Moss, 2002; Modaress, 2006). In a Fault Tree, a system or component failure is graphically presented as a logical relationship with possible causes that can contribute to the system or component failure. 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 forms of logic gates that determine the effects of the basic events; the AND-gate and OR-gate are most commonly used in the FT. A fault tree is usually adapted to its top event and includes only the most credible faults as assessed by the risk analyst(s) and may not represent all possible system failure causes (Vesely et al., 1981). Amrozowicz et al. (1997); Kum and Sahin (2015); Laskowski (2015); Pietrzykowski (2007) present the application of fault trees to analyze marine accidents.

A Bayesian Network is a Directed Acyclic Graph (DAG) that satisfies the Markovian condition. A DAG is a directed graph with no cycles and the Markovian condition for Bayesian network states that every node in a Bayesian network is conditionally independent of its non-descendants, given its parents. A DAG consists of two sets: the set of nodes and the set of directed edges. In a BN, nodes represent random variables while the edges represent conditional relationships (casual relationships) between the connected nodes (Jensen and Nielsen, 2007; Ben-Gal, 2007). Several studies are found in the literature that apply BN to analysis various types of marine accidents (Afenyo et al., 2017; Hänninen, 2014). However, no studies are found that have conducted formal risk analysis of marine logistics support in distant harsh environments.

Based on the literature review, the main logistics issues in a remote platform operating in harsh environment are identified as:

- There are two modes for logistics operation: helicopter and marine vessels. Helicopter operation is limited by the environmental conditions and remoteness. Long-distance operation of helicopters is particularly risky.
- Marine vessels are relatively reliable and versatile alternative to helicopters. Although, quick response is not possible by a vessel from an onshore base to remote locations.
- Risk associated with regular and emergency marine logistics operation is not well-quantified or understood as no publicly available formal risk analysis has been conducted to date.
- There is considerable uncertainty associated with operations and risk assessment for remote harsh environments due to the lack of operational experience in such operating conditions.
- A viable solution is yet to be developed to address the logistics challenges of harsh environment remote offshore development.

1.3 Summary and Research Hypothesis

In summary, there are two significant levels of problem identified in the literature associated with development of increasingly distant and harsh offshore projects. A significant high level problem is the lack of a risk based methodology to evaluate the most significant risks and the most effective solutions to these risks in dollar terms; and the low level problem is a lack of well-developed concept solutions for the problem of long travel distances from shore base to offshore site.

The goal of this research is to address these two problems by setting up a more general risk analysis methodology and evaluating the methodology by performing a specific case study. This will consist of an in-depth study to identify the challenges of offshore logistics operations, assessing risk, and developing a feasible solution to the identified logistics issues, all focused on the specific case of a remote harsh environment installation. The work is concentrated on logistical supports and operations as this is identified in the literature as the longest term and most risk-prone stage in the life of an offshore development. Figure 1.2 illustrates the organization of the thesis that includes the goal, objectives and associated research tasks.

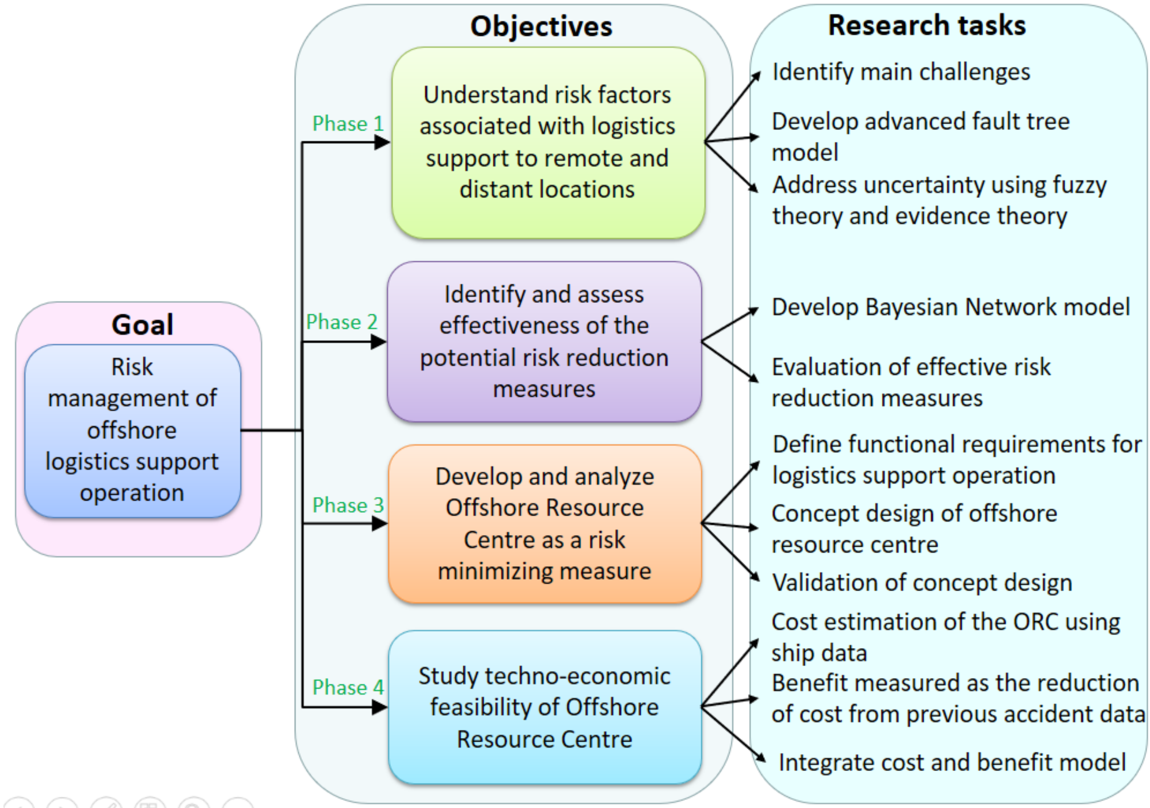

Figure 1.2: Objectives of this research

The research is divided into four phases in which each phase addresses one of the objectives identified in Figure 1.2. In phase one, a risk model is developed to find the most significant factors related to failure of a marine logistics support operation in a remote harsh environment. A probabilistic approach is adopted using advanced fault-trees, which is integrated with fuzzy logic theory and evidence theory to address the limitation of existing data. This work serves to identify the higher risk aspects of the logistics operations for remote offshore developments and to improve the methodology for offshore risk assessment in the face of limited historical data.

In the second phase, a framework is developed to identify the most effective risk reduction measures for logistics operations. A Bayesian approach is implemented in this framework that considers the interdependencies among the contributing risk factors. This work introduces the idea of conditional dependence as a means of improving the risk reduction analysis procedure.

In the next phase of this research, using the knowledge gathered from the phase 1 and phase 2 analyses, a specific solution in the form of an intermediate offshore resource centre (ORC) is proposed for effective risk reduction. This novel solution is conceived as a practical means of providing the most effective risk reduction measure to address the identified highest risk aspects of a logistics operation in a remote harsh environment.

In phase four, the research develops a cost-benefit analysis procedure for the proposed solution that can guide decision making to assess the feasibility of any proposed risk reduction measure. This provides a novel engineering economics approach to assessing the viability of a proposed risk reduction strategy. As a case study using the developed methodology, the costed risk of a hypothetical offshore blowout incident is estimated using a loss function developed based on historical blowout events. The capital and operating costs of the solution proposed in phase 3 are estimated and the net benefit, expressed in economic terms, of the risk reduction strategy is presented. This provides both a methodology and a demonstration of utility through a specific solution case.

The Flemish Pass Basin is chosen as the case study location. This drilling location is approximately 500 nautical miles east of St. John's, Newfoundland and Labrador. The water depths in this area range from 500 to over 3,000 m (Project Description Summary – Equinor, 2016). Figure 1.3 shows the location of Flemish Pass drilling project. This region exhibits harsh environmental conditions including intense storms and the presence of ice (sea ice and icebergs). The distance between the onshore supply base and the offshore drilling location is sufficiently long to be considered remote and needing special consideration.

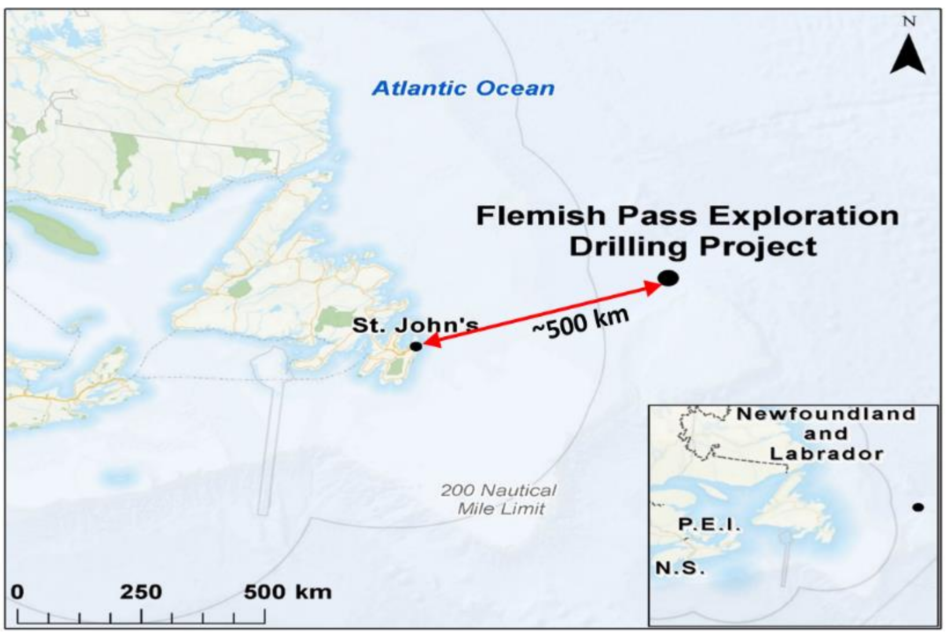

Figure 1.3: Exploration drilling location in the Flemish Pass Basin (Source: Canadian Environmental Assessment Agency, date retrieved: August 21, 2018)

1.4 Novelty and contribution

This research identifies the logistical challenges of remote offshore operation in harsh environments. The contributions includes new methodology to better understand the risk profile of a new development scenario with minimal background data, formal analysis process with better understanding of conditional dependence to evaluate possible measures to overcome these challenges. The work also develops a unique practical solution to the logistical problem, in the form of the ORC Concept, and finally provides a novel method of evaluating the cost effectiveness of this or any proposed risk reduction measure. A brief description of the contributions and novelties of this research is provided below.

Logistics risk model development

A novel marine logistics risk model is developed to support offshore operations is challenging environmental conditions. The model identifies and considers key failure modes and develops appropriate failure models. The model relaxes the assumption of independence of causes. Data and model uncertainties are considered. Application of the proposed model is demonstrated through a case-study concerning a remote North Atlantic offshore operation.

Solution for logistics risk

A Bayesian network (BN) based risk model is developed to consider interdependencies and conditional relationships among the contributing factors to an offshore logistics failure. Appropriate risk management strategies are proposed to support marine logistics operations. This allows identification and ranking of the major sources of risk.

Concept development of proposed solution

An intermediate offshore resource centre (ORC) as a potential solution to the logistics problem is presented. A vessel or platform of this type and functionality has not been previously developed or proposed. The purpose, functional requirements and the conceptual design of an ORC are discussed. A modular volume-limited ship design concept is adopted to determine the principal particulars of the ORC. The concept design of the ORC is tested and validated for the vessel stability and mooring requirements.

Framework for risk-based cost-benefit analysis

A new framework is developed for risk-based cost-benefit analysis that helps to assess the net financial cost or benefit of using a system, such as an ORC, as a risk reduction strategy for remote offshore developments. This presents a structured but flexible approach that can be easily modified for different scenarios. The methods can be applied to any potential risk mitigation system.

1.5 Organization of the thesis

The thesis is written in manuscript format that includes four journal papers as chapters. Table 1.1 shows the papers written during the course of this research and establishes their connection to the overall objectives listed in Figure 1.2.

Table 1.1: Organization of the thesis

Papers as chapters	Research objectives	Associated tasks
Chapter 1: Introduction. Not applicable for publication.	• To specify Problem statement of offshore logistics support operation. • To present overall research objectives and organization of the thesis.	• Conduct literature review. • Identify knowledge gaps. • Define research objectives and research hypothesis.
Chapter 2: Development of risk model for marine logistics support to offshore oil and gas operations in remote and harsh environments.	• To develop a framework for formal risk analysis of logistical problem. • To provide an understanding of associated risk.	• Identify key challenges from literature survey. • Develop probabilistic risk model using advance fault trees. • Identify model and data limitations. • Address data uncertainty using fuzzy theory and evidence theory.
Chapter 3: A conditional dependence-based marine logistics support risk model.	• To identify potential risk reduction measures. To assess the feasibility of each measure.	• Develop a conditional dependence-based risk model that integrates reduction measures. • Address data limitation using evidence-based approach. Detect effective measure using sensitivity analysis.
Chapter 4: Conceptual development of an offshore resource centre in support of remote harsh environment operations.	• To develop the concept of the identified viable measure (Offshore resource centre) from previous study.	• Define functional requirements for logistics support operation. • Identify suitable platform to meet this purpose. Concept design of offshore resource centre. • Validation of concept design.

Table 1.1: Organization of the thesis (continued)

Papers as chapters	**Research objectives**	**Associated tasks**
Chapter 5: Risk-Based Cost Benefit Analysis of Offshore Resource Centre to Support Remote Offshore Operations in Harsh Environment.	• To develop a framework to assess economic viability of offshore resource centre.	• Estimate cost of the ORC using historical ships data. Develop loss function of an accident scenario (blowout). Benefit measured as the reduction of cost a blowouts due to ORC. • Cost-benefit comparison. Analyze sensitivity of blowout probability with the net risk reduction.
Chapter 6: Summary, Conclusion and Future Works. Not applicable for publication.	• To provide a summary, outcome of this research and recommendations for future work.	• Conclusion drawn from the overall study. • Acknowledge limitations of this study and possible future work.

An outline of each chapter is presented below.

Chapter 2 identifies the risk contributing factors of marine logistics operation in a remote harsh environment. An advanced fault tree analysis is used to develop the logical relationships among these factors and a sensitivity analysis is conducted to rank the most critical factors that cause emergency response failure. The fault-tree model is integrated with fuzzy logic theory and evidence theory to address the limitation of existing data.

Chapter 3 presents a Bayesian network model that establishes a causal relationship among factors contributing to offshore logistics risk and possible risk reduction measures. A framework is developed to identify the most effective risk reduction measures for logistics operations. An uncertainty analysis is conducted based on evidence theory to address inherent data limitation.

Chapter 4 proposes a specific solution in the form of an intermediate offshore resource centre (ORC) for effective risk reduction based on the most critical factors identified in Chapter 3. The functional requirements of an ORC are defined in an aim to reduce logistical risk of remote offshore operation in challenging environments. Conceptual development of the ORC includes overall sizing estimation and validation of preliminary stability and mooring requirements.

Chapter 5 provides a framework for risk-based cost-benefit analysis. The cost model is the life-cycle cost of the proposed ORC, which is estimated based on historical ship data using regression analysis. The benefit model is expressed as a loss function of blowout incidents, which is a function of response time and the distance from the nearest logistics support. This study presents an integrated framework that evaluates the net benefit, expressed in economic terms, of the risk reduction strategy is presented.

Chapter 6 concludes this thesis with a summary of key developments and conclusions. It presents recommendations for potential future work.

A co-authorship statement is provided at the beginning of each chapter. The statement describes the contribution of each author in different stages of the research.

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2. Development of Risk Model for Marine Logistics Support to Offshore Oil and Gas Operations in Remote and Harsh Environments

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Co-authorship statement

A version of this manuscript has been published in Ocean Engineering. The lead author Md Samsur Rahman performed the literature review, developed the fault trees for the offshore logistics support risk model, collected failure probability data, performed the model analysis, generated the results, and prepared the draft of the manuscript. The co-author Faisal Khan helped in developing and testing the risk models, reviewed and corrected the models and results, and contributed in preparing, reviewing and revising the manuscript. The co-author Arifusalam Shaikh also helped in the development of the model. All co-authors including Salim Ahmed and Syed Imtiaz reviewed and provided feedback on the manuscript. Md Samsur Rahman revised the manuscript based on the co-authors' feedback and during the peer review process.

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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. The key factors that affect such operations are identified and failure models are developed. 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 and a robust risk model to help developing innovative risk management strategies to support offshore operations.

Keywords: Logistics risk, offshore safety, fault tree analysis, fuzzy set theory, evidence theory.

2.1 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 kilometres east of St. John’s, Newfoundland and Labrador (Figure 2.1). 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 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.

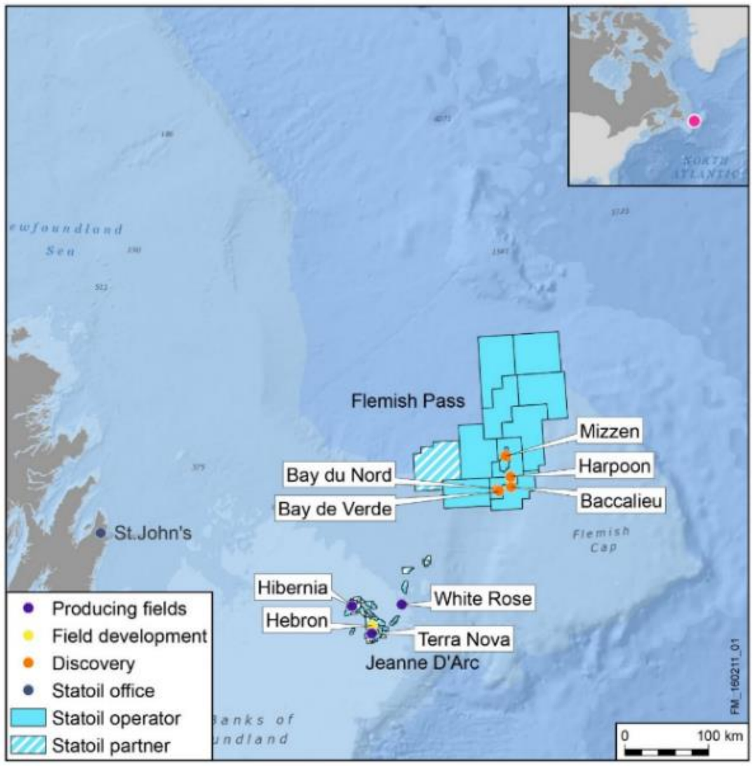

Figure 2.1: Location of Statoil exploration drilling project in the Flemish Pass Basin

(Source: News/ June 10, 2016/Statoil Canada Limited)

The rest of this paper is organized as follows. Section 2.2 broadly describes the methodology for risk analysis of marine logistics operations and an illustrated example is presented in section 2.3. Section 2.4 discusses results and conclusions are provided in section 2.5.

2.2 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 Figure 2.2. 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.

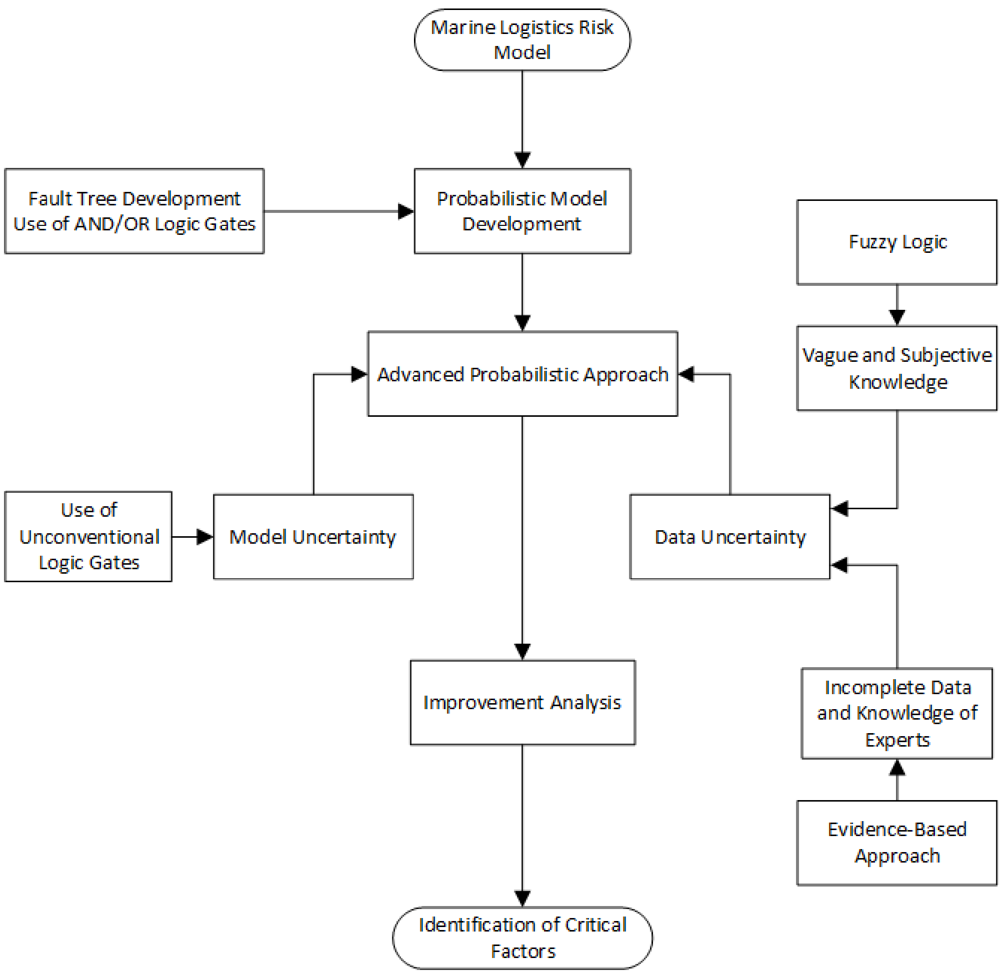

Figure 2.2: The proposed framework for marine logistics support risk modelling in harsh environments

2.2.1 Logical modelling of marine logistics support

2.2.1.1 *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 Figure 2.3. 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.

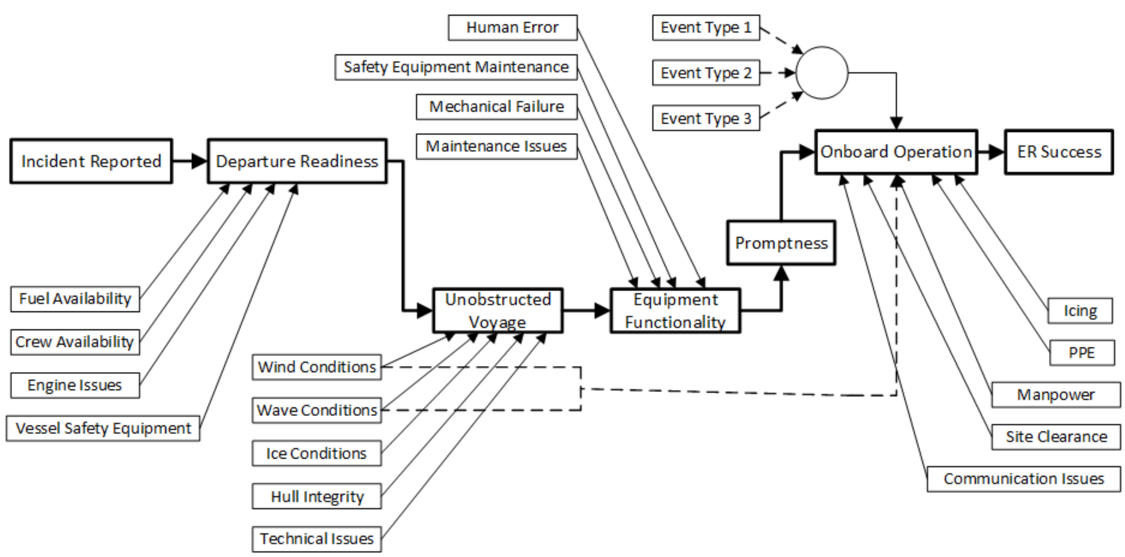

Figure 2.3: Logistics operation or emergency response (ER) process

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); Khorasani (2015).

Unobstructed voyage

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

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 & 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.

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.

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.

2.2.1.2 *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 Figures 2.4 to 2.7. 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 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 2.4. 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.

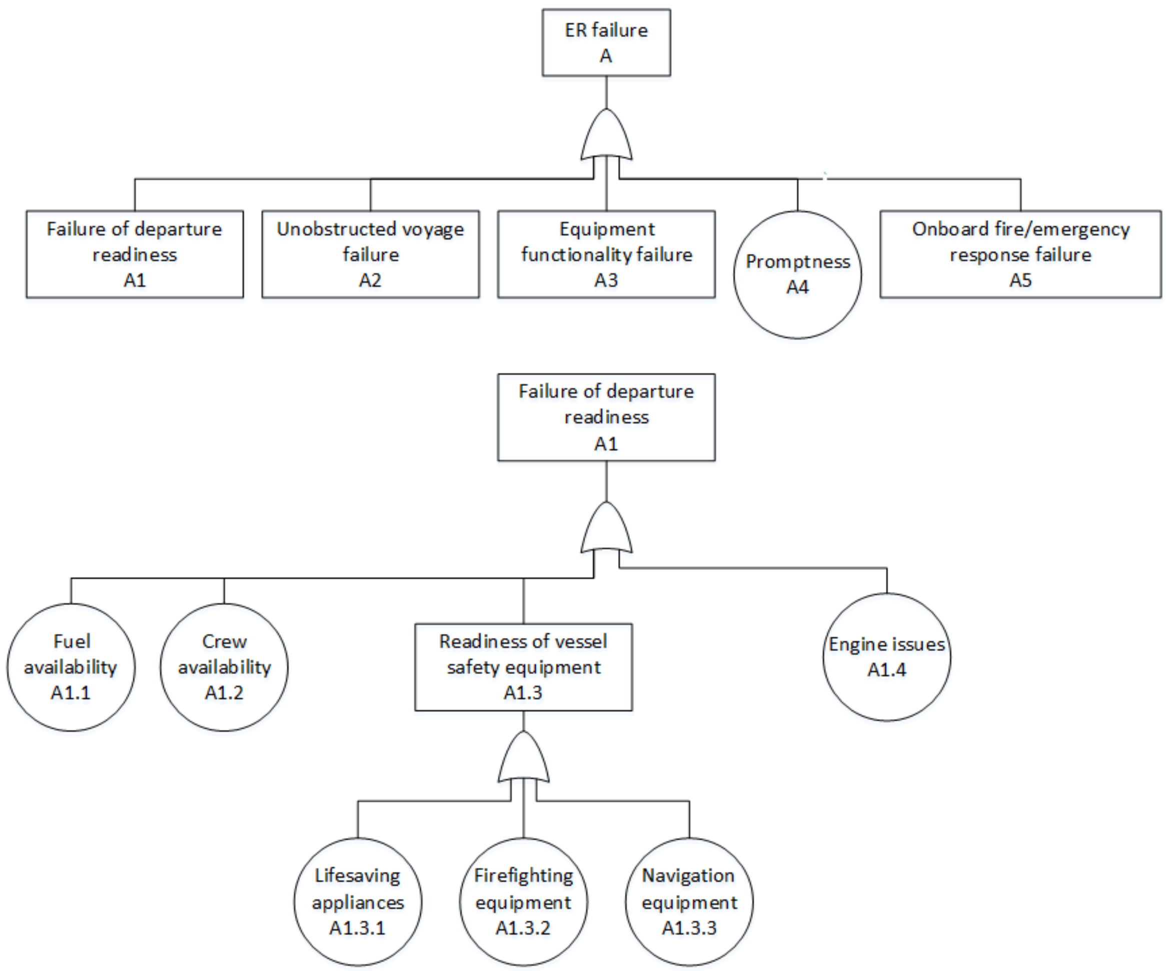

Figure 2.4: Fault Tree model for logistics support to an offshore facility in remote harsh environment

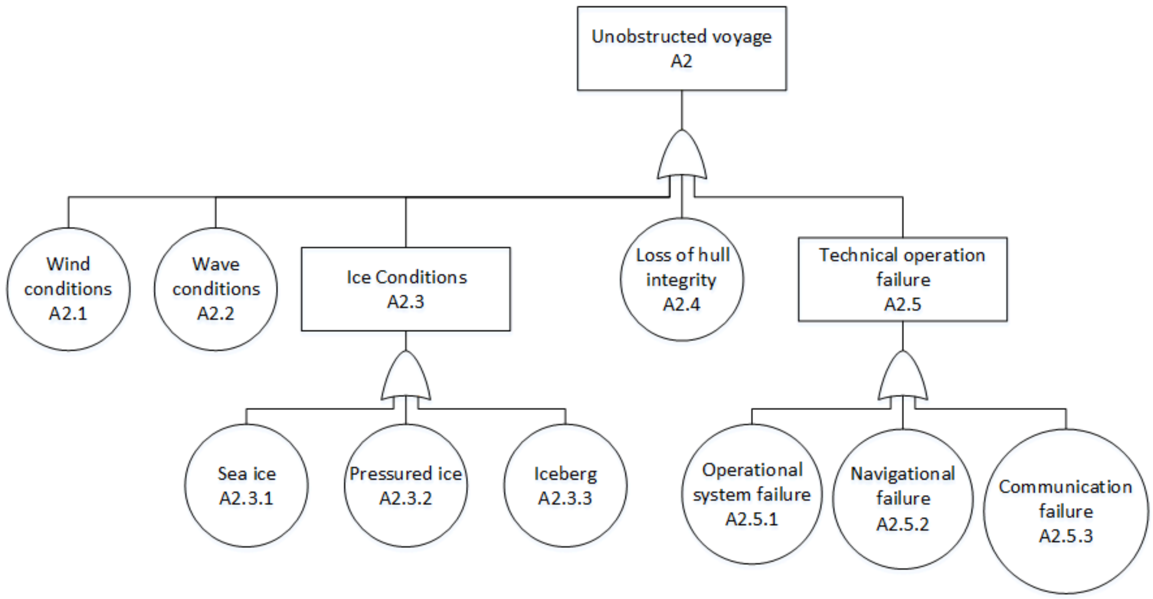

Figure 2.5: Fault Tree model for unobstructed voyage failure

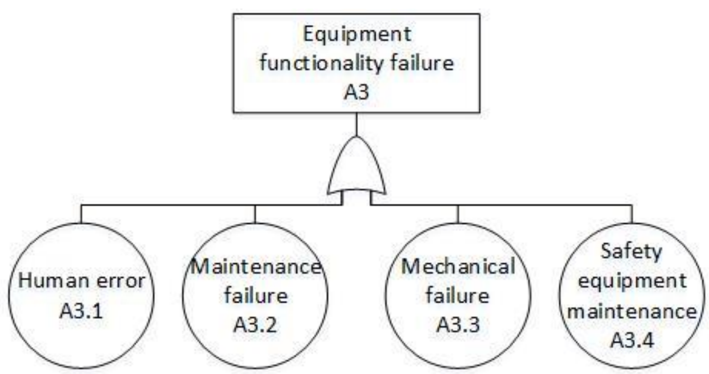

Figure 2.6: Fault Tree model for equipment functionality failure

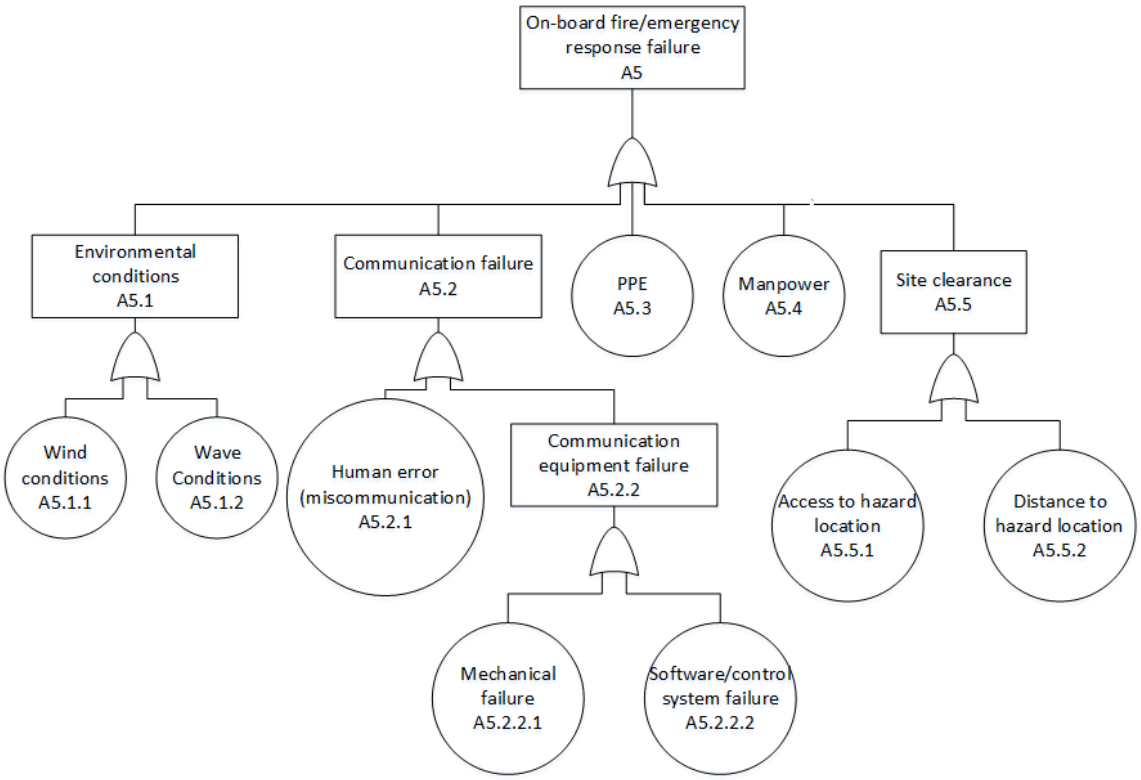

Figure 2.7: Fault Tree model for on-site operational failure

2.2.2 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 2.1. 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.

Table 2.1: 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

Table 2.1: Model assumptions in the traditional FT model and approaches to relax the assumptions (continued)

	Model Assumptions	Approach to Relax Assumptions	Reference
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., 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

Table 2.1: Model assumptions in the traditional FT model and approaches to relax the assumptions (continued)

	Model Assumptions	Approach to Relax Assumptions	Reference
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.	

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 Figures 2.8 to 2.10.

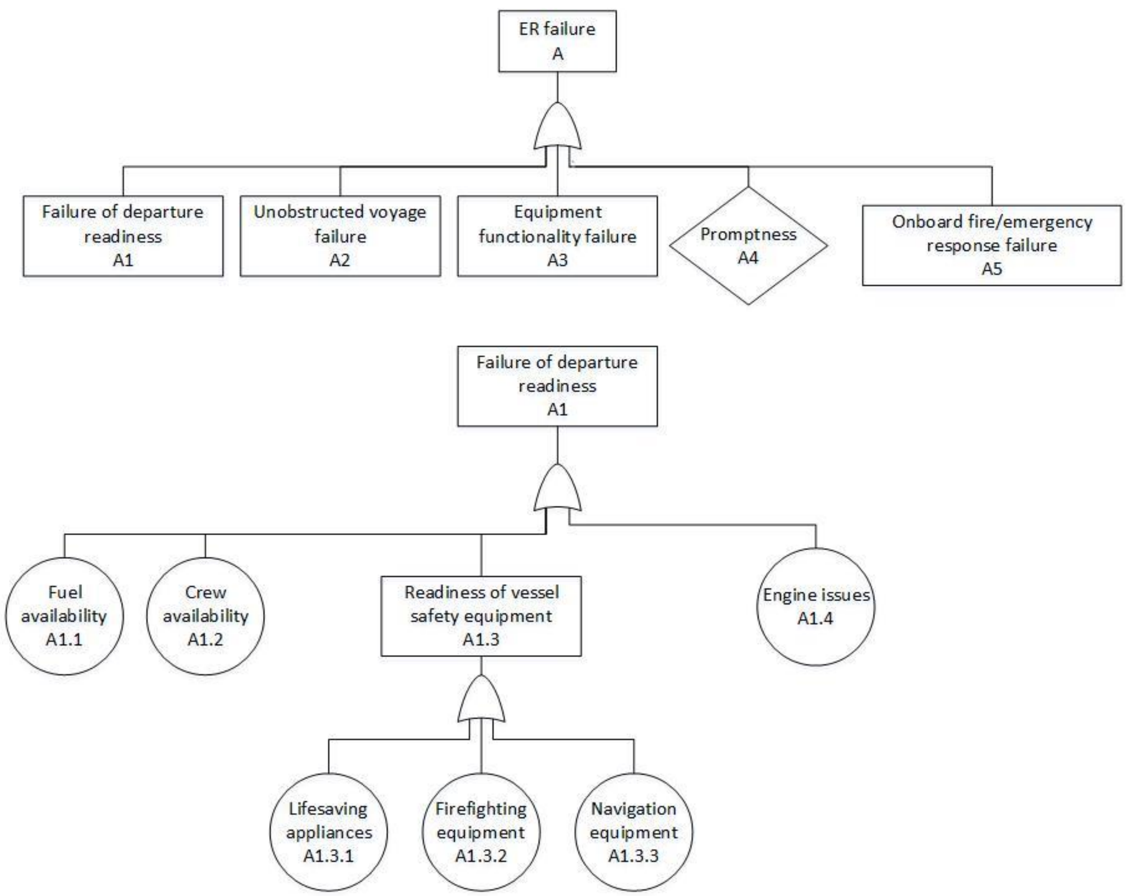

Figure 2.8: Modified Fault Tree model for marine logistics support in remote harsh environment

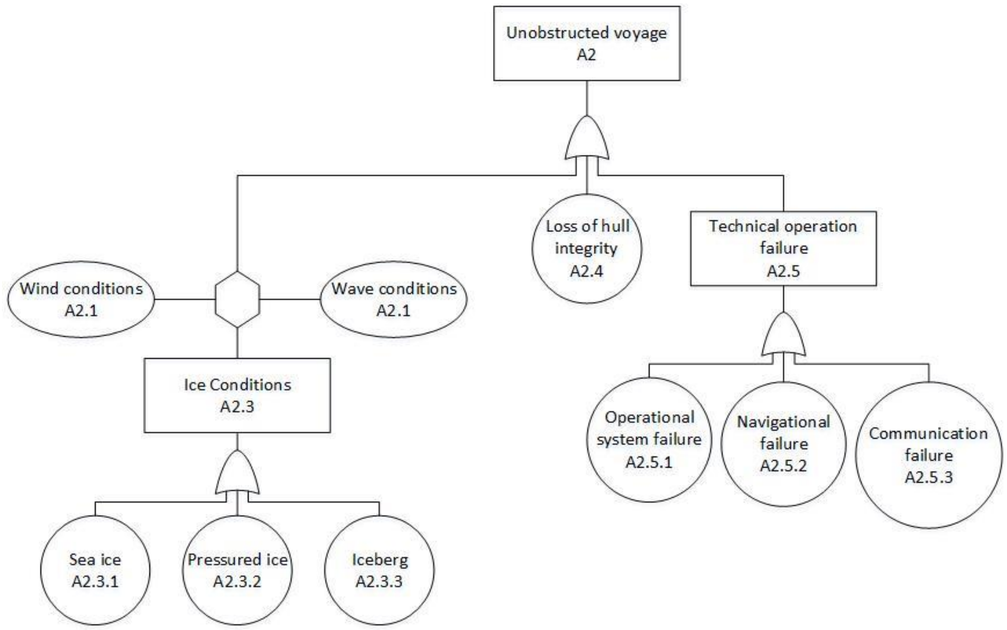

Figure 2.9: Modified Fault Tree model for unobstructed voyage failure

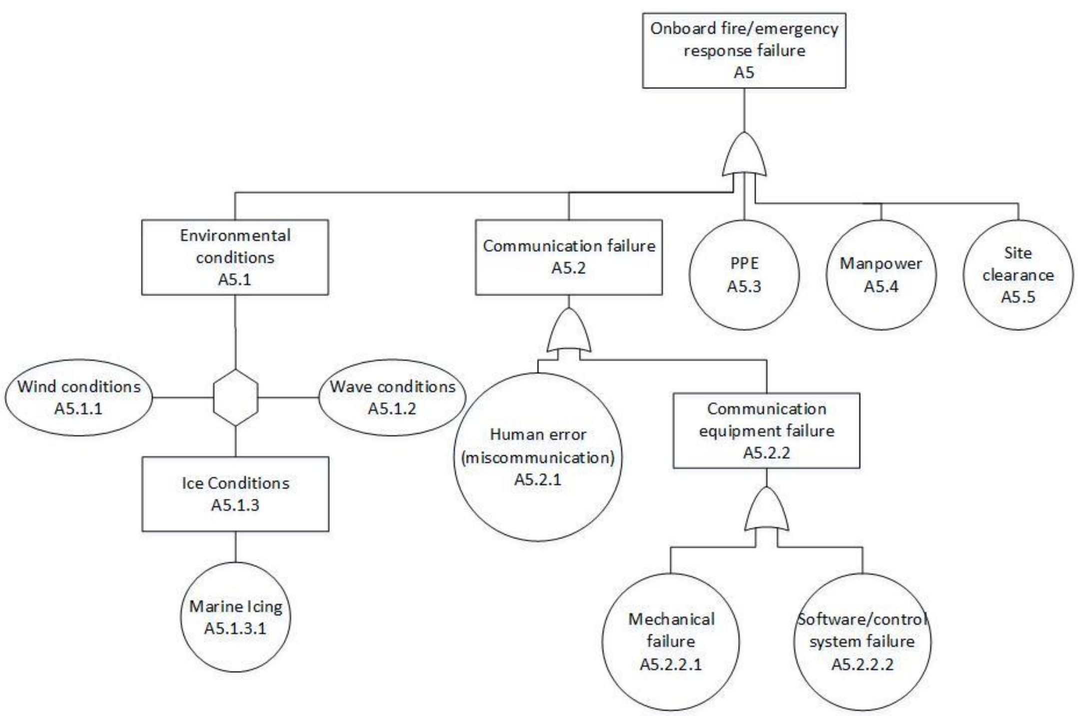

Figure 2.10: Modified Fault Tree model for onsite operational failure

2.2.3 Data Uncertainty

Table 2.2 summarizes the data related assumptions that may result in uncertainty in risk assessment. In the advance FTA, a fuzzy-based 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.

Table 2.2: 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

2.2.3.1 *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. Figure

2.11 illustrates a TFN and the fuzzy intervals are obtained using the following equation 2.1 (Ferdous et al., 2011; Pan and Yun, 1997):

$$p_\alpha = [p_l + \alpha(p_m - p_l), p_u - \alpha(p_u - p_m)] \tag{2.1}$$

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

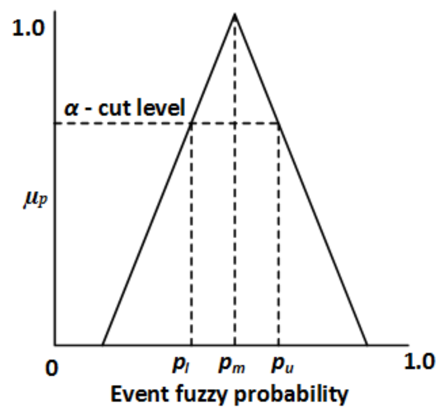

Figure 2.11: Representation of triangular fuzzy number of an event

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 Table 2.3, and (3) Defuzzification of top event failure probability to a crisp value.

Table 2.3: 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	$p_l^{\alpha} = \prod_{i=1}^{n} p_{il}^{\alpha}$; $p_u^{\alpha} = \prod_{i=1}^{n} p_{iu}^{\alpha}$

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).

2.2.3.2 *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.
(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.

2.3 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 2.4.

Table 2.4: 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

The top event failure probability is estimated for both the traditional and advanced fault tree models and presented in Table 2.10. 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 report, 2001).

2.3.1 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 2.5, where the confidence interval is chosen as 95% (α=0.95).

Table 2.5: Triangular Fuzzy Number at α=0.95

		Triangular Fuzzy Number (TFN)			95% Confidence (α=0.95)	
Basic Event	Fuzzy Number "around"	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)	---	---	---	---	---	---
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

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 2.6.

Table 2.6: 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

2.3.2 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 2.7.

Table 2.7: Basic probability assignments

Basic Event	Expert 1 Failure {F}	Success {S}	{SF}	Expert 2 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

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 2.8.

Table 2.8: 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

Three important characteristics, namely, belief, plausible value and Bet of the top event are calculated and presented in Table 2.9.

Table 2.9: 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

2.4 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 2.10.

Table 2.10: 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

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 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 2.2 is used to evaluate this index:

$$F_{IM}(P_T, P_{Ti}) = (P_{il(T)} - P_{il(Ti)}) + (P_{iu(T)} - P_{iu(Ti)}) \tag{2.2}$$

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 Figure 2.12. 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.

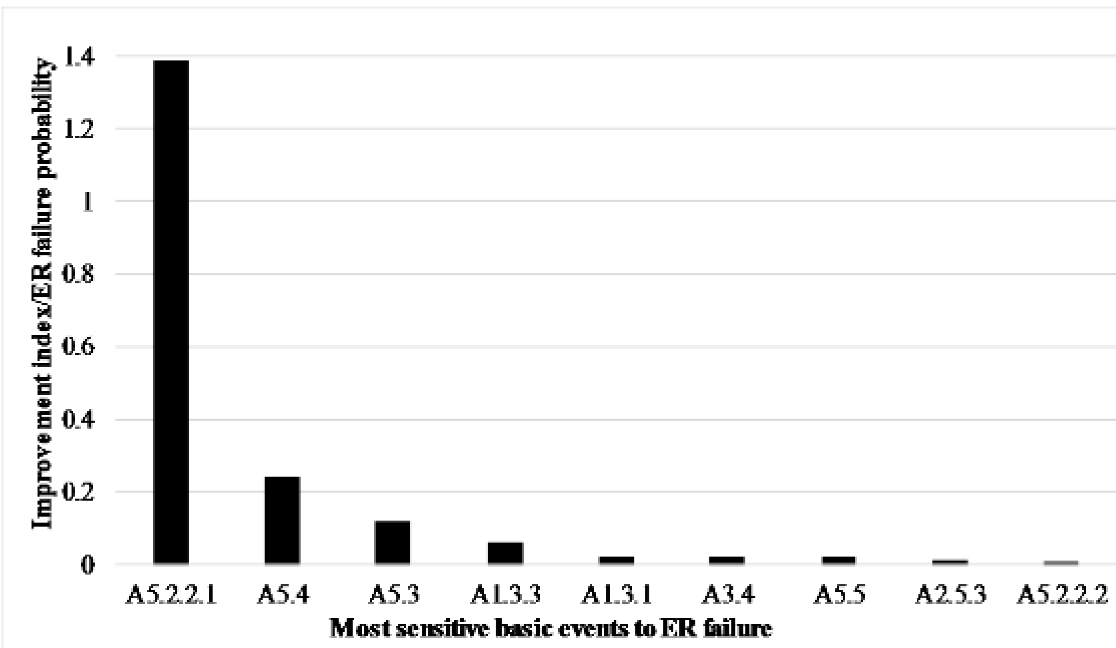

Figure 2.12: Ratio of Improvement Index and ER failure probability of basic events (See Table 2.4 for legends)

2.5 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 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 interdependencies and uncertainty handling capacity. Therefore, BN modelling of the ER operation could be a promising future study.

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3. A Conditional Dependence-based Marine Logistics Support Risk Model

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A version of this manuscript has been published in the Journal of Reliability Engineering and System Safety. The lead author Md Samsur Rahman performed the literature review, developed the Bayesian network model for offshore logistics support failure, collected conditional probability data and integrated this data into the model, performed the model analysis, generated the results, and prepared the draft of the manuscript. The co-author Faisal Khan supervised and helped in developing and testing the BN risk model, reviewed and corrected the models and results, and contributed in preparing, reviewing and revising the manuscript. Arifusalam Shaikh, Salim Ahmed and Syed Imtiaz reviewed and provided feedback on the manuscript. Md Samsur Rahman revised the manuscript based on the co-authors' feedback and during the peer review process.

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Abstract

Industries and researchers have renewed interest in the Arctic as well as the sub-Arctic regions due to the proven hydrocarbon reserves. The main challenges of operations in these regions arise due to their remoteness and extreme weather conditions. These conditions also put major challenges to plan emergency logistics support, which is currently offered either by helicopters or marine vessels. This paper analyzes the risk-based marine logistics support model in an offshore facility operating in the far northern (sub-arctic) region. A Bayesian network (BN) approach is used to develop the risk model considering interdependencies and conditional relationships among the contributing factors. Exploration in the Flemish pass basin located offshore Newfoundland and Labrador, Canada, is selected as a case study to demonstrate the methodology. The study identifies the critical elements of a marine logistics operation that need attention to reduce its associated risk. The corresponding safety measures are identified and implemented into the risk model. Appropriate risk management strategies are proposed to support marine logistics operations.

Keywords: Marine logistics, offshore risk management, fault tree, Bayesian network.

3.1 Methodology to Develop Logistics Risk Model

Harsh environments represent extreme weather conditions, which are not favorable for human, infrastructure and habitat (Khan et al., 2014a). The northern frontiers have the harshest environmental conditions with the presence of various ice features, extreme cold temperature, freezing rain, high wind and wave, and marine fog (Walsh, 2008; Arctic Marine Shipping Assessment, 2009). The exploration and development of natural resources in these regions face significant safety and integrity challenges, which are identified as the lack of details in construction and operation standards, restricted operating conditions, presence of different ice features such as pack ice and icebergs, remoteness, human factors, and knowledge and data scarcity (Khan et al., 2014b). There are several standards and practices such as ABS 2010, ISO 19906:2010, NORSOK S-002, Barents 2020 available for the operation in harsh environments. However, there is a lack of design and operational guidelines for further north that must consider the additional distance and more extreme environmental conditions (Hamilton, 2011; Meling, 2013). The planning and procedure for logistics supply and support during emergency is an important area of research to ensure safe operation, which is the focus of this study. There is a need to assess the risk, improve understanding and knowledge as well as develop new strategies and technologies prior to launching operations in these regions (Milaković et al., 2014; Malykhanov and Chernenko, 2015; Borch, 2018; Uthaug, 2018).

Logistics for offshore operations are provided by supply vessels and helicopters. In general, marine vessels are used for transporting materials and supplies from an onshore supply base to support offshore exploration activities. Helicopters are used to transport personnel and light cargo to and from offshore platforms. Besides the routine logistics for supply, the role of emergency response (ER) is to support emergency evacuation when the platform needs to be abandoned. In addition, the ER team needs to reach the platform to restore its production during a disturbance or perturbation. Prompt response is required to enhance the resilience of an offshore system and minimize the severity of an accident, which can be critical due to the distance and environments. Faster response can be provided by helicopter than support vessel, however the use of helicopter is limited when the distance is too long, and subject to weather conditions. Also, it cannot be used if the platform itself is sinking or any situation that is not safe for the helicopter to land or winch. The accident rates in the offshore helicopter industry are still at least one order of magnitude greater than those of commercial fixed-wing operations (Oil & Gas UK, 2017; OGP, 2010). The crash of a helicopter is almost always considered as a very serious event - often leading to fatalities and serious economic loss (Sutton, 2014; Okstad et al., 2012; Olsen and Lindøe, 2009; Hokstad et al., 2001; Vinnem, 2011, 2010). Baker et al. (2011) published an article about helicopter crashes related to oil and gas operations in the Gulf of Mexico, where an average of 6.6 crashes occurred per year during 1983 – 2009 and resulted in a total of 139 fatalities. During that period, bad weather led to a total of 29 crashes, which accounted to 40% of the 139 deaths. According to the Civil Aviation Authority and Oil & Gas UK records, there were 73 UK Continental Shelf offshore commercial air transport (CAT) accidents reported from 1976 to 2013 in which a total of 119 fatalities occurred. 11% of these accidents occurred due to external factors such as icing, turbulence, wind shear, thunderstorm or bird strike. These problems are particularly acute at night, when the accident rates are considerably higher than that in the daytime. Knowledge of the hazards and risks associated with such accidents is very limited (Ross and Gibb, 2008). This is aggravated by the expected increase in nighttime offshore helicopter activities associated with, for example, the beginning of the exploration of oil and gas in polar regions (Nascimento, 2014). Marine vessel becomes the only mode for transporting logistics if these circumstances are considered. The feasibility of marine logistics operation in the remote harsh environment is not well-understood and needs to be further studied (Khan et al., 2014a, 2014b).

In a previous work (Rahman et al., 2019), a failure model of marine logistics operation was developed using the fault tree where the inherent limitations of the model and available data were identified. An attempt has been made to address the model limitations using advanced fault tree analysis using unconventional logical gates. Researchers have adopted the fuzzy theory and the evidence theory to address the data limitations (Zadeh, 1965; Ferdous et al., 2009, 2011; Klir and Yuan, 2001; Yager, 1987). The current work presents a Bayesian approach to address model dependencies. Although fault tree is useful for initial stage of model development, the Bayesian approach benefits from several advantages over fault tree (Bobbio et al., 2001; Simon et al., 2007). BN has a more flexible framework that can address conditional dependencies among the contributing factors. It allows backward analysis and probability updating which means the updated information can be incorporated to the model (Boudali, 2005; Weber, 2010). This feature helps to make the model dynamic and more realistic (Khakzad et al., 2011, Yuan et al., 2015). Detail discussion about this is presented in the methodology. The goal of this work is to establish risk management strategies for marine logistics operation, which is an extension of the previous work.

The rest of this paper is organized as follows. Section 3.2 broadly describes the methodology for risk management of marine logistics operations. A case study is presented in section 3.3. Section 3.4 discusses the possible safety measures to reduce risk and their application to the model. Conclusions are provided in section 3.5.

3.2 Methodology

Risk assessment is a systematic approach that helps in the decision-making process for an operation (ABS, 2010). It has two elements, frequency assessment and consequence assessment, which can be evaluated either qualitatively or quantitatively. Various methods and tools are available for assessing risk, however choosing the right approach is a key for useful risk assessment (Crowl and Louvar, 2002; Andrew and Moss, 2002; Modaress, 2006). A Bayesian approach is used for modelling marine logistics support risk in this study. Bayesian network is a Directed Acyclic Graph (DAG) that satisfies the Markovian condition. A DAG is a directed graph with no cycles and the Markovian condition for a Bayesian network states that every node in a Bayesian network is conditionally independent of its non-descendants, given its parents. A DAG consists of two sets: the set of nodes and the set of directed edges. In a BN, nodes represent random variables while the edges represent conditional relationships (casual relationships) between the connected nodes (Jensen and Nielsen, 2007; Ben-Gal, 2007). If an edge connects from node *A* to node *B*, then variable of *B* depends on the variable of *A*. Hence, node A and node B are referred to as a parent and a child, respectively. A BN represents a joint probability distribution (JPD) over a set of random variables. Each variable has a finite set of mutually exclusive states i.e. binary states (success/failure). Mathematically, if a BN specifies the unique joint probability distribution $P(A)$ over a set of random variables $A = \{A_1, A_2, ..., A_n\}$, then $P(A)$ given by the product of all conditional probabilities specified in BN (equation 3.1):

$$P(A) = \prod_{i}^{n} P(A_i \mid pa(A_i)), \tag{3.1}$$

where $pa(A_i)$ are the parents of A_i in the BN and $P(A)$ reflects the properties of the BN (Pearl, 1988).

A BN can be used to find out updated knowledge about the state of a variable given the evidence of another variable and thus Bayes' theorem applies. According to the Bayes' theorem, the posterior probability of a variable A given the evidence E can be expressed as (equation 3.2):

$$P(A|E) = \frac{P(A) \times P(E|A)}{P(E)}, \tag{3.2}$$

where $P(A)$ is the prior probability of A, $P(E|A)$ is the likelihood function that represents the likelihood of the evidence E if the hypothesis A is true and $P(E)$ is the normalizing factor that represents the prior probability of E when the evidence itself is true. $P(E)$ can be calculated using the law of total probability (equation 3.3):

$$P(E) = P(E|A)P(A) + P(E|\bar{A})P(\bar{A}), \tag{3.3}$$

A and $\bar{A}$ are mutually exclusive that $(A\ , \bar{A}) = 0$. An example of a simplified BN model is presented in Figure 3.1 to illustrate the application of Bayes' theorem and inter-dependence among the variables. A marine operational system failure (C) may occur due to poor visibility (A) and human failure (B). In Figure 3.1(a), A and B are marginally independent, which means poor visibility has no influence on human error whereas Figure 3.1(b) represents that A and B are dependent given C as the likelihood of human error may increase if poor visibility occurred. The CPTs are presented in Figure 3.1 and the probability of operational system failure, $P(C)$ can be calculated using equation 3.3 for both cases such that $P(C) = P(A, B)P(C|A, B) + P(A, \bar{B})P(C|A, \bar{B}) + P(\bar{A}, B)P(C|\bar{A}, B) + P(\bar{A}, \bar{B})P(C|\bar{A}, \bar{B})$. The occurrence probability of operational system failure, $P(C)$ is calculated as 0.0168 and 0.0181 when the parent nodes, A and B are independent and dependent, respectively. Assuming the operational system failure has already occurred, the posterior probability of the occurrence of poor visibility can be calculated using equation 3.2.

$$P(A|C) = \frac{P(A) \times P(C|A)}{P(C)} = \frac{0.01 \times 0.19}{0.0168} = 0.1134$$

Similarly, the posterior probability of human error occurrence becomes $P(B|C) = 0.9463$. Now, in Figure 3.1(b), human error is conditionally dependent on poor visibility, then the updated probability of human error would be: $P(B) = P(B|A)P(A) + P(B|\bar{A})P(\bar{A}) = 0.25\times0.01 + 0.1\times(1 - 0.01) = 0.1015$. The posterior probability of the occurrence of poor visibility and human error becomes 0.1796 and 0.9586, respectively. Hence, it is evident that the conditional relations of the nodes significantly change the outcome.

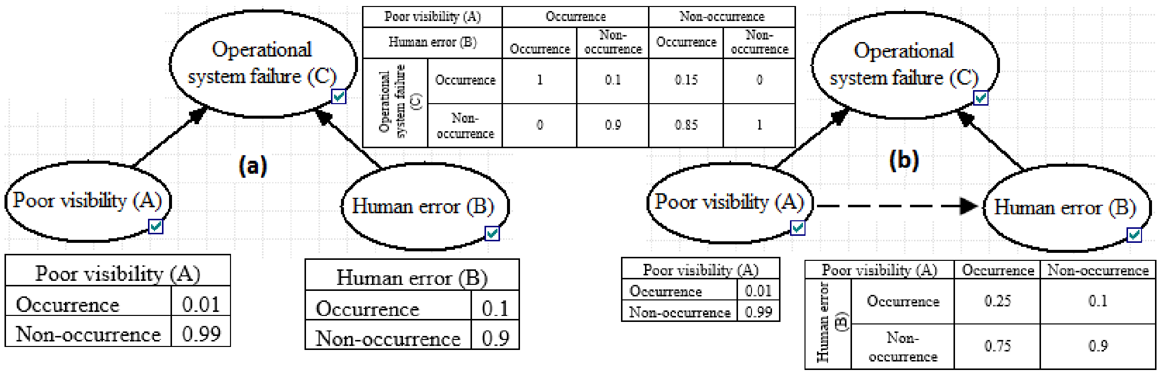


Figure 3.1: Simplified BN showing CPTs and inter dependency between nodes

This concept has been implemented to address the conditional dependence of the contributing factors of marine logistics support risk model. Figure 3.2 illustrates the proposed framework and explanation of the main steps are provided in the followings.

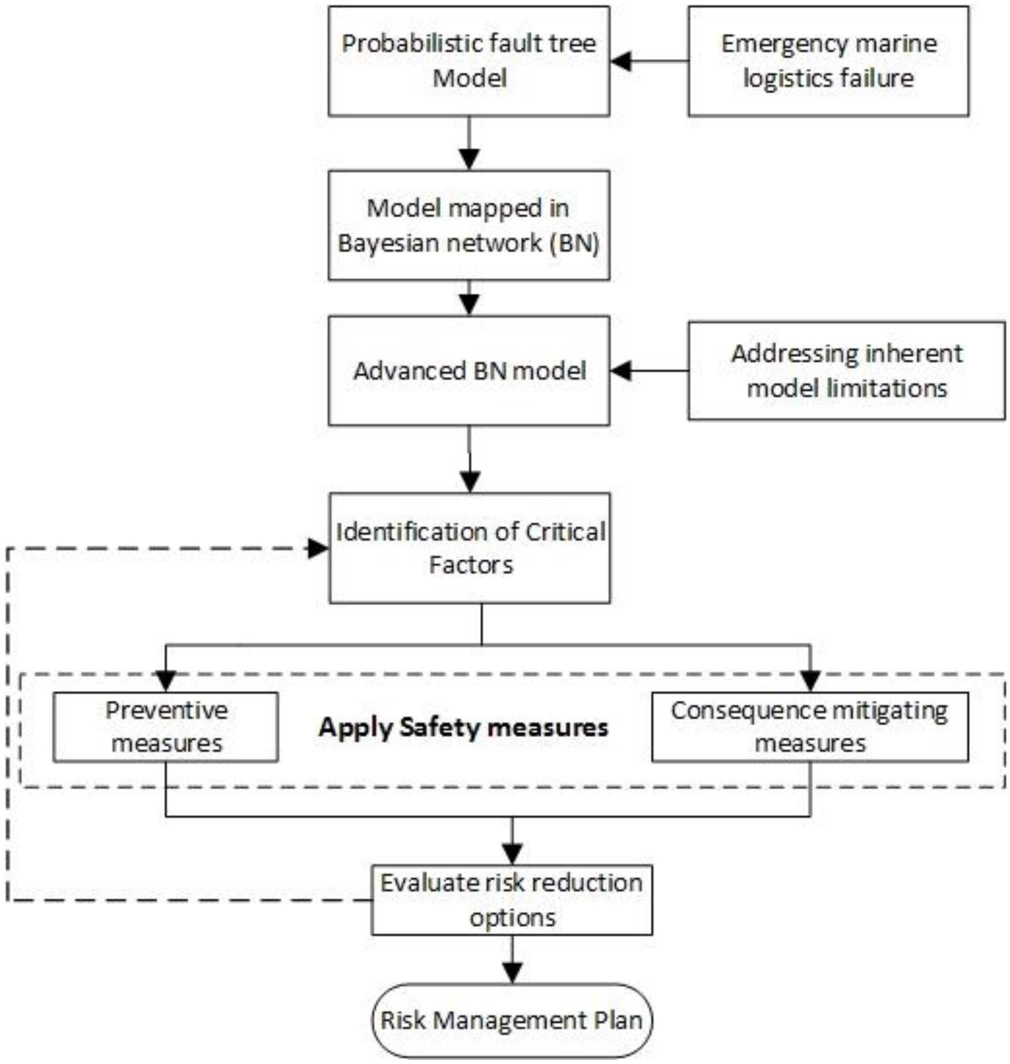


Figure 3.2: The proposed methodology for marine logistics risk management in harsh environments

Step 1 - Development of marine logistics risk model using Bayesian network: The BN model is developed based on the concept of marine logistics operation and the fault tree model presented in the previous study. A marine logistics operation consists of the following main 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 (Figure 3.3). The parameters associated with each phase of a logistics operation are selected based on detailed discussion with the stakeholders, which include individuals such as offshore oil and gas operators, marine transportation consultants, subject matter experts, and academics in the related fields. Stakeholders have reviewed these parameters and the model is developed based on the logical relationships among these key contributing parameters. These parameters are further confirmed through a detail literature review and the outcome of which is presented in (Rahman et al., 2019).

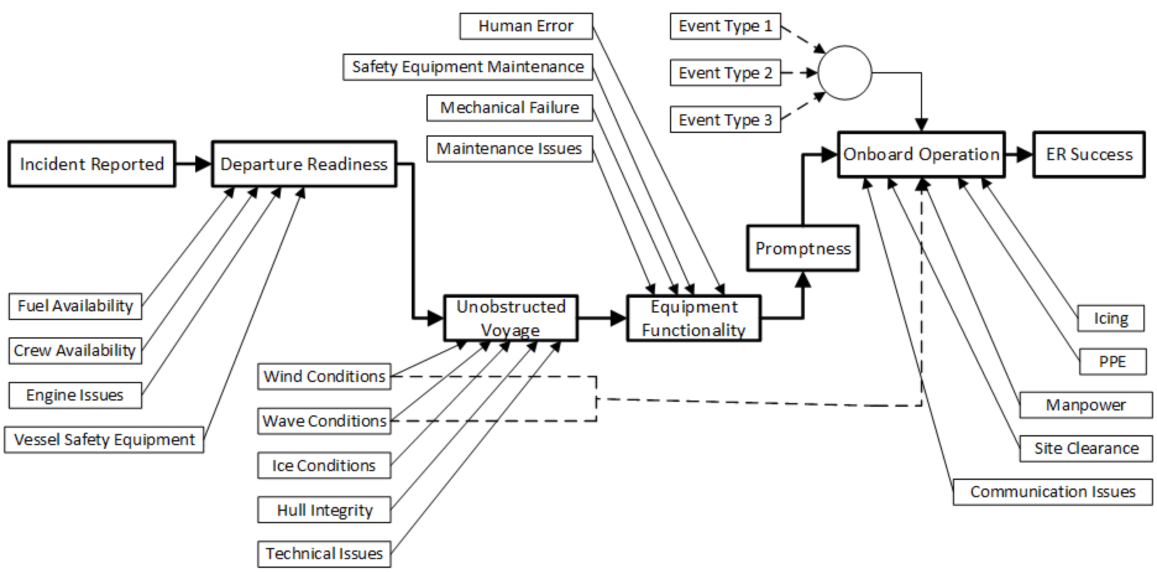


Figure 3.3: Logistics operation or emergency response (ER) process (Rahman et al., 2019)

The primary FT model (Rahman et al., 2019) is mapped to a BN based on the approach described by Khakzad et al., 2013. The failure probabilities of primary events of the FT model are assigned to the corresponding root nodes of the BN model as prior probabilities. The logical relationships of the intermediate nodes and the leaf nodes with the root nodes are defined by the conditional probability tables (CPT). The primary BN model is presented in Figure 3.4.

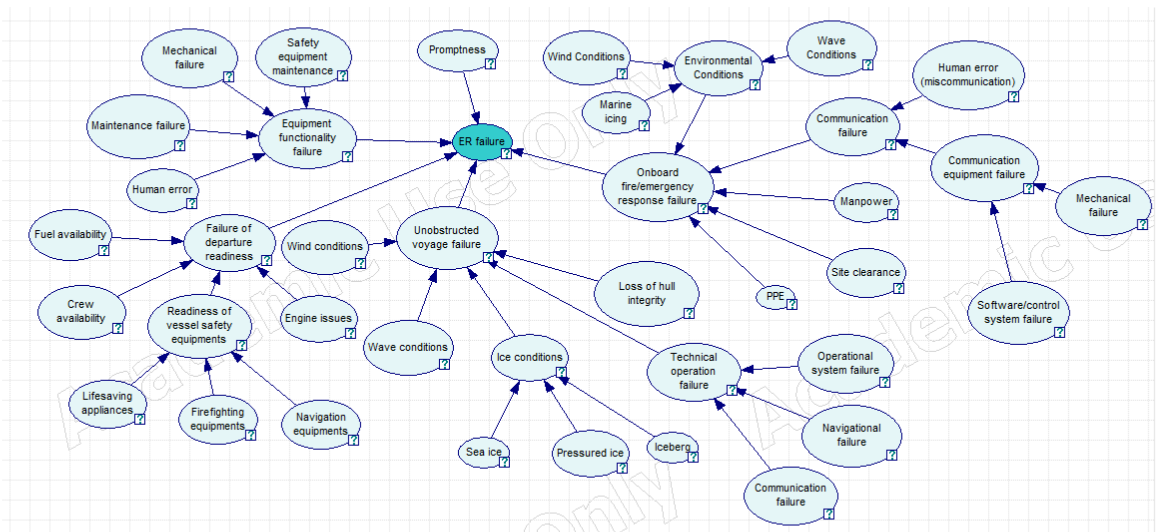


Figure 3.4: The basic BN model for marine offshore logistics operation

Step 2 - Advanced Bayesian network model: The primary BN model suffers from several limitations which are: 1) Interdependencies among the contributing factors are not considered, 2) Failure due to promptness is not developed and 3) Logical relationships among the factors are developed based on simplified OR/AND-gates that do not always reflect the real scenarios. The following approaches are considered to address these limitations:

1) The following interdependencies are addressed in the model:

- Equipment functionality failure may affect onboard fire/emergency response.
- Engine issues may affect both ship departure readiness and unobstructed voyage.
- Human error may result operational system failure, communication failure, onboard fire/emergency response and equipment functionality failure.
- Existing environmental conditions may affect response time, unobstructed transit of vessel and onsite operation.
- Ice conditions are related to wind and wave conditions.

In this study, “human error” is considered as a single parameter. However, the human error could be considered as a series of nodes that would represent different modes of human related failure. A detail study can be performed as a human reliability analysis (HRA) exercise aiming to identify the causes and sources of human errors and to provide an estimation of the human error probabilities (HEPs). A performance shaping factor (PSF) is often used in HRA that systematically quantifies the potential influences of a factor on human performance. Aspects of an individual’s characteristics, environment, organization or task specifically influence human performance, and change the likelihood of human error (Blackman et al., 2008). In a more detailed study of human factors for marine operational failure, the BN model can be further expanded into multiple modes based on PSFs and their dependencies could also be considered. Some of the detail studies of the influence of human factors in a harsh offshore operation were presented in Musharraf (2014), and Norazahar (2017). An illustrative example is presented in Figure

3.5 to explain how human error probability can be estimated for different scenarios. In an emergency response to a remote offshore installation, human error may occur due to various mode of human failure such as wrong detection, failure to act and inconsistent response. The corresponding PSFs and probabilities of these scenarios are presented in Table 3.1.

Table 3.1: Performance shaping factors of different scenarios of human error

Scenarios	**Performance shaping factor (PSF)**	**Probability of occurrence**
Wrong detection	Lack of training/experience (PSF1)	0.1
	wrong procedure (PSF2)	0.05
Failed to act	Distraction (PSF3)	0.06
	Stress (PSF4)	0.09
	Physical condition (PSF5)	0.03
Inconsistent response	Lack of training/experience (PSF1)	0.1
	Complexity (PSF6)	0.07

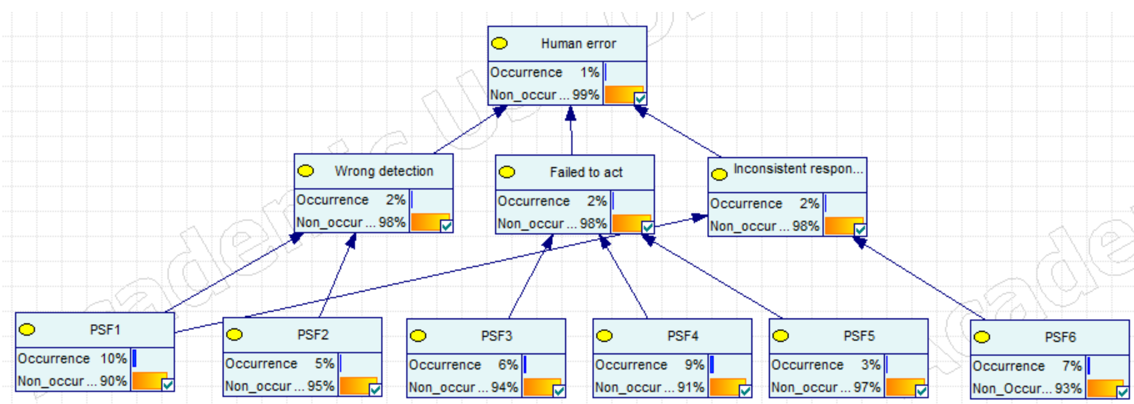


Figure 3.5: A sample BN for estimating human error during offshore onboard operation

2) Promptness is further developed as a function of the distance between the platform and the onshore base. In addition, promptness failure could happen if the ship fails to depart or disrupts during its voyage.

3) Probabilistic gates such as noisy gates are 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 failure probability can be optimized. The CPTs are modified based on the experts' opinion who have managed several offshore safety related projects and have several years of experience in the relevant area. Evidence theory can be used to integrate multiple experts' opinion. This also helps to deal with the uncertainties and considers the conflict of knowledge between the experts. Evidence theory was first proposed by Dempster (1967) and later expanded by Shafer (1976), which is also known as the Dempster-Shafer Theory (DST). In DST, the main three functions are: the basic probability assignment function (*bpa or m*), the belief function (*Bel*), and the plausibility function (*Pl*). An event probability is defined with a set of lower and upper bound values, which are denoted as belief (*Bel*) and plausibility (*Pl*), respectively, and a mass (*bpa)* is assigned for the uncertainty or ignorance about that event. According to the Dempster rule of combination, multiple belief functions from different sources are combined through their basic probability assignments (*m*) that considers that knowledge sources are independent and uses the conjunctive operation (AND) for aggregation. For example, if the $m_1(P_A)$ and $m_2(P_B)$ are two sets of evidence for the same event collected from two

different experts, the combination (called $m_{12}(P_i)$) is calculated from the aggregation of two bpa's $m_1(P_A)$ and $m_2(P_B)$ in the following manner (equation 3.4):

$$m_{12}(P_i) = \begin{cases} 0, & P_i = \emptyset \\ \frac{\sum_{P_A \cap P_B = P_i} m_1(P_A) \times m_2(P_B)}{1-k}, & P_i \neq \emptyset \end{cases} \tag{3.4}$$

where k represents basic probability mass associated with a conflicting opinion. The Dempster rule of combination uses $(1 - k)$ as normalizing factor that ignores all conflicting evidence through normalization. Further details about DST and the combination rules of evidence can be found in Shafer (1986), Sentz and Ferson (2002), Ferdous et al. (2011), Rahman et al. (2019). The modified BN model is presented in Figure 3.6: The modified BN model for marine offshore logistics operation.

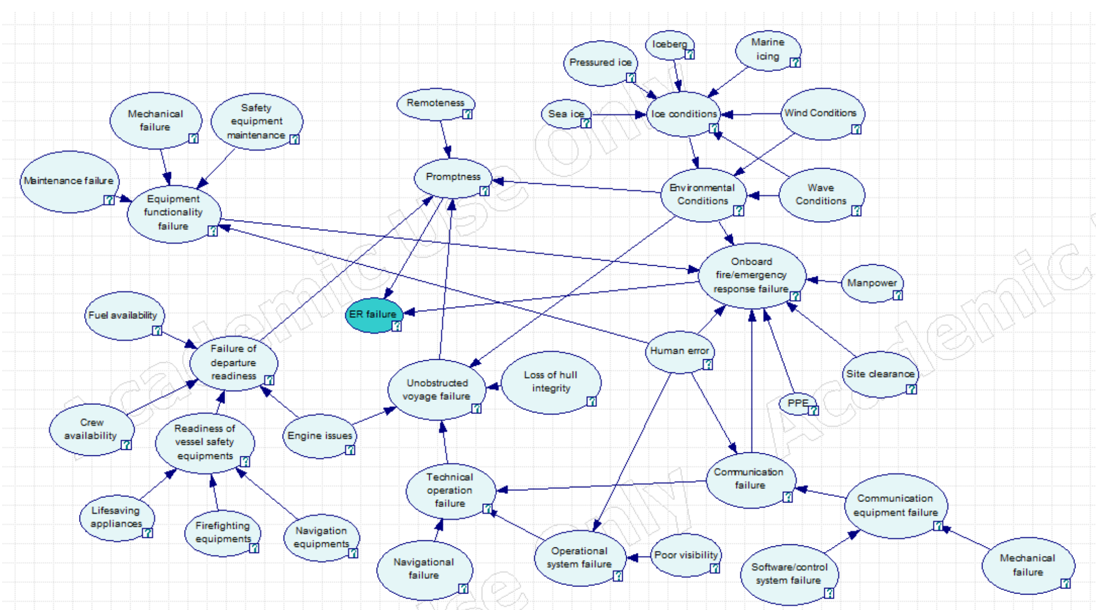


Figure 3.6: The modified BN model for marine offshore logistics operation

Step 3 – Critical factor analysis: Sensitivity analysis is very important to identify the most critical factors. First, backward analysis or diagnostic analysis can be performed where the states of some nodes are instantiated, and the updated probabilities of conditionally dependent nodes are calculated (Bobbio et al., 2001; Khakzad et al., 2013). The ratio of posterior and prior probabilities can be used as an index for identifying the critical factors (Abimbola, 2016). For example, the ratio of posterior and prior probabilities of poor visibility and human error in the model presented in Figure 1.1(a) can be calculated as: $P(A|C)/P(A)$ = 0.1134/0.01 = 11.34 and $P(B|C)/P(B)$ = 0.9463/0.1 = 9.46. This suggests that operational system failure is relatively more sensitive to poor visibility than human error.

Alternatively, importance measure can be found by evaluating the risk reduction worth or top event's sensitivity. It is defined as the decrease in the probability of the top event, given that a particular event does not occur. To obtain the risk reduction worth for an event, the top event failure probability is quantified by assigning zero probability of failure to the given primary event (Khan et al., 2001; Khakzad et al., 2011).

Step 4 – Safety measures and risk management: In the context of risk management, safety measures are classified into three types: inherent, engineered and procedural (Khan et al., 2003). In safety related decision making, inherent safety measures, that avoid hazards instead of controlling them, are usually given priority when compared to the other types of safety measures (Amyotte et al., 2009; Kletz, 2003). Aside from the inherent safety measures, engineered safety measures are the addition of new safety equipment that can be either passive or active systems depending on the nature of their functions. Passive safety measures are preferred than active safety measures as they help to reduce the effect of an accident and do not depend on external controlling or activating systems. Next, procedural safety measures control hazards through personnel education, training and management. Such measures include standard operating procedures, safety rules and procedures, personnel training, and management systems to improve human performance (Yuan et al., 2015).

Safety measures can be applied in two stages: prevention and mitigation. To estimate the complete risk, a consequence model is required along with probabilistic failure model as the risk can be calculated as (equation 3.5):

$$Risk = \sum_{i=1}^{n} P_i \times L_i \, , \tag{3.5}$$

where P_i refers to the probability of the i-th consequence and L_i stands for the corresponding losses, which are usually converted into equivalent financial losses.

Once the critical factors for a system have been identified, specific safety measures can be assigned for each factor based on experts' suggestions. The effect of each safety measures in overall risk reductions are estimated that helps to develop the risk management strategies. The percentage of risk reduction (*%RR*) can be calculated using equation 3.6 (Yuan et al., 2015).

$$\%RR = (R - R_{SMi})/R \times 100 \tag{3.6}$$

where R is the risk of marine logistics failure before application of safety measures; R_{SMi} is the risk of the system after the application of the i-th safety measure. A higher *%RR* value of any safety measure indicates that it can reduce risk more effectively. An illustrated example of the proposed methodology is provided in the following sections.

3.3 Application of the Proposed Methodology

3.3.1 Description of the Case Study

A case study is presented in this section to illustrate the application of the proposed model. The exploration in the Flemish Pass Basin is a suitable example to describe the scenarios envisaged in this study. This drilling location is approximately 480 kilometres east of St. John’s, Newfoundland and Labrador. The water depths in this area are ranging from 500 to over 3,000 m (Project Description Summary – Equinor, 2016). Figure 3.7 shows the location of Flemish Pass drilling project.

Figure 3.7: Exploration drilling location in the Flemish Pass Basin (Source: Canadian Environmental Assessment Agency, date retrieved: August 21, 2018)

This region exhibits harsh environmental conditions including intense storms and the presence of ice (sea ice and icebergs). Superstructure icing can also occur between December and March because of the temperature, wind and wave conditions. Restricted visibility due to fog is also common, especially in the months of spring and summer, when warm air masses overlie the cold ocean surface. The worst visibility conditions are experienced in July. During the months of winter, restricted visibility can also be caused by snow in addition to fog and mist (ISO 19906:2010). In addition, the distances between the onshore supply base and the offshore drilling locations impose extra challenge for emergency logistics support that needs special considerations.

3.3.2 Probability Data

The modified BN model (Figure 3.6) represents the failure model of emergency logistics support for this case study. The failure probabilities of the contributing factors are listed in Table 3.2, which is based on a comprehensive literature survey (Rahman et al., 2019).

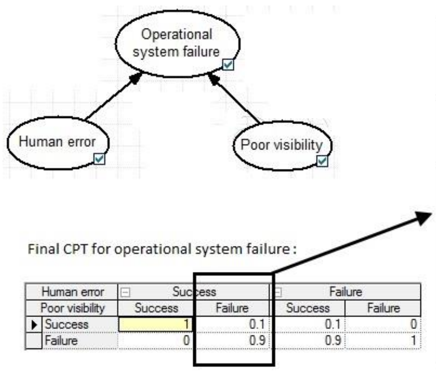
Table 3.2: Failure probabilities

Basic events	**Probability of failure**	**Reference**
Fuel availability	3.97×10^{-4}	Kum and Sahin, 2015
Crew availability	3.97×10^{-4}	Kum and Sahin, 2015
Lifesaving appliances	1.00×10^{-3}	Bercha et al., 2003
Firefighting equipment	3.97×10^{-4}	Kum and Sahin, 2015
Navigation equipment	2.55×10^{-3}	Antao et al., 2006
Engine issues	2.6×10^{-4}	Kum and Sahin, 2015
Wind conditions	6.00×10^{-3}	Apostolos et al., 2009
Wave conditions	1.97×10^{-4}	Apostolos et al., 2009
Sea ice	2.75×10^{-3}	Kum and Sahin, 2015
Pressured ice	5.94×10^{-2}	Kum and Sahin, 2015
Iceberg	1.00×10^{-2}	Apostolos et al., 2009
Marine icing	1.50×10^{-4}	Expert opinion
Loss of hull integrity	1.33×10^{-4}	Christou and Konstantinidou, 2012
Poor visibility	7.00×10^{-4}	Apostolos et al., 2009
Navigational failure	2.00×10^{-6}	Amrozowicz et al., 1997
Human error	3.00×10^{-4}	Apostolos et al., 2009
Maintenance failure	1.00×10^{-4}	Expert opinion
Mechanical failure	5.46×10^{-2}	Bercha et al. 2003
Safety equipment maintenance	1.00×10^{-3}	Expert opinion
Remoteness	3.00×10^{-2}	Expert opinion
Mechanical failure (Communication)	1.00×10^{-5}	Apostolos et al., 2009
Software/control system failure	4.00×10^{-4}	Apostolos et al., 2009
PPE	5.00×10^{-3}	Expert opinion
Manpower	1.00×10^{-2}	Expert opinion
Site Clearance	1.00×10^{-3}	Expert opinion

The failure probabilities of several factors are collected from Kum and Sahin (2015). The primary sources of their marine accident/incident data are Marine Accident Investigation Branch (MAIB)'s reports; accident data were analyzed by fuzzy fault trees to estimate occurrence probabilities. This study considered 65 arctic marine accidents reported from 1993 – 2011. Another source of data is Apostolos et al. (2009), where traditional probabilistic risk analysis tools such as the fault tree and the Bayesian network were used for calculating failure probabilities. Amrozowicz et al. (1997) presented a probabilistic assessment of a ship's navigational failure, where an analysis of tanker grounding using the fault tree was conducted. The probability data related to lifesaving appliances are obtained from Bercha et al. (2003). This information was deduced from full scale lifeboat launch data that was carried out in Canada and the United Kingdom. Navigation equipment failure data are collected from Antao et al. (2006); this source presents fault tree models of accident scenarios of Ro-Ro vessels for cargo and passengers. Christou and Konstantinidou (2012) conducted an analysis of oil and gas related accidents; data used in this study was primarily collected from the Health and Safety Executive (HSE), MAIB, Worldwide Offshore Accident Databank (WOAD), and DNV. However, these sources provide only an example to choose a sensible value for demonstrating the methodology.

Expert elicitation is required when data are not available, or it is difficult to measure the accuracy of data. It is a formal procedure for obtaining and combining knowledge. There are various methods available for experts' knowledge elicitation. Some of the fundamental works related to expert elicitation were published in Cooke (1991) and O'Hagan (1998). A scoring system is introduced in this process based on the scores of experts' judgements and the level of certainty of their beliefs. The available methods to aggregate elicited judgements can be either behavioral, where the members of the expert panel interact with each other to reach a single distribution, or mathematical where individual assessments are analytically processed to obtain a combined probability distribution (Clemen and Winkler, 1999). An example of a behavioral approach is the Delphi method; the mathematical techniques include axiomatic and Bayesian approaches. In this paper, the evidence-based approach or the Dempster-Shafer Theory is implemented to aggregate the data collected from two experts. Both experts have PhD in the relevant subject. Expert 1 has 15-20 years of experience in offshore oil and gas related projects, whereas expert 2 has 5-10 years of experience in logistics operation. Since the data is collected from individuals, there may be some uncertainty in the data. The application of DST can help with this issue, which can address missing data and conflicting subjective data. This also helps to integrating data from multiple 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. Besides, it should be mentioned that a larger number of experts from heterogeneous backgrounds would have been better to gain more reliable results in this study. The aim of this study is to demonstrate the application of the approach, not to claim the accuracy of the outcome. This process can be repeated and further improved with a more detailed survey. Similar approach can be applied to combine probability information from more than two experts when available.

Since expert judgements are epistemic/subjective in nature, uncertainties may exist in the data. Several literatures suggested implementation of the evidence-based approach to overcome this type of uncertainties (Ayyub and Klir (2006), Sentz and Ferson (2002), Ferdous et al. (2009). An illustrated example to aggregate both experts' conditional probability data for operational system failure using the Dempster rule of combination is presented in Figure 3.8. In DST, a belief mass (*bpa or m*) for each event is acquired from multiple sources i.e. expert 1 and expert 2. The *bpa* represents the degree of experts' belief for each subset. In Figure 3.8, expert 1 reported the conditional probability of operational system failure is 75% true and 9% false when no human error occurred but failure due to poor visibility happened. Mathematically, this is written as $m(\{T\}) = 0.75$, $m(\{F)\} = 0.09$ and $m(\{T,F\}) = 1-m(\{T\})-m(\{F\}) = 0.16$. Similarly, for expert 2, $m(\{T\}) = 0.60$, $m(\{F)\} = 0.17$ and $m(\{T,F\}) = 0.23$. The data acquired from two experts are aggregated using the DS rule presented in equation 3.4. The term $(1 - k)$ can be interpreted as a normalization factor for the conflict among the evidential information. In DS rule of combination, it is assumed that the two sources of information are independent of each other.



	Operational system failure Human error - *S* & Poor visibility - *F*		Expert 1 (m_1)		
			Failure (*F*)	Success (*S*)	Ignorance (*FS*)
			0.75	0.09	0.16
Expert 2 (m_2)	Failure (*F*)	0.6	0.45	0.054	0.096
	Success (*S*)	0.17	0.1275	0.0153	0.0272
	Ignorance (*FS*)	0.23	0.1725	0.0207	0.0368
	Degree of uncertainty (*k*)	0.1815			
	$\sum m_1 m_2$		0.719	0.0632	0.0368
	Dempster's combination (m_{12})		0.8778	0.0772	0.0450
		Belief structure			
		Bel (F)	*Pl (F)*	*Bel (S)*	*Pl (S)*
	Dempster-Shafer	0.8778	0.9228	0.0772	0.1222
	Bet (Crisp value)	0.9003		0.0997	

Figure 3.8: Combination of conditional probabilities from the experts using DS rule

From the *bpas*, the lower bound and upper bound of an interval can be determined by equation 3.7 and equation 3.8, which are referred as belief (*Bel*) and plausibility (*Pl*), respectively. The belief (*Bel*) or lower bound for a set P_A is the sum of all the basic probability assignments of the proper subsets P_B of the set of interest P_A, i.e., $P_B \subseteq P_A$. The plausibility (*Pl*) or upper bound is the sum of all the *bpas* of the sets P_B that intersect the set of interest P_A, i.e., $P_B \cap P_A \neq \emptyset$. Hence,

$$Bel(P_A) = \sum_{P_B \subseteq P_A} m(P_B) \tag{3.7}$$

$$Pl(P_A) = \sum_{P_B \cap P_A \neq \emptyset} m(P_B) \tag{3.8}$$

The belief structure of operational system for the given condition is calculated as [0.8778, 0.9228] and [0.0772, 0.1222] for failure and success, respectively. The conditional probabilities obtained from this example is used to estimate the belief structure of ER failure from the BN model in Figure 3.6. The estimated lower bound (*Bel*) and upper bound (*Pl)* of the occurrence of ER failure is 0.0848 and 0.0849, respectively. The failure probability of emergency response estimated in the example reflects slight deviation, however this an illustration to demonstrate how the uncertainty of expert knowledge can be accounted using this approach.

3.3.3 Critical Factor Analysis

In this section, the most critical factors of marine logistics operations are identified. One of the advantages of BN is probability updating that means the updated information (evidence) of some events can be utilized to estimate the probabilities of other factors of a system. Here, the occurrence of the logistics failure is set as evidence. Next, the probability of all contributing factors can be updated accordingly that gives the corresponding posterior probabilities. The ratio of posterior and prior probabilities can be calculated in which the higher value indicates the most sensitive factors. Figure 3.9 illustrates the posterior probabilities of the contributing factors if the emergency logistics support fails.

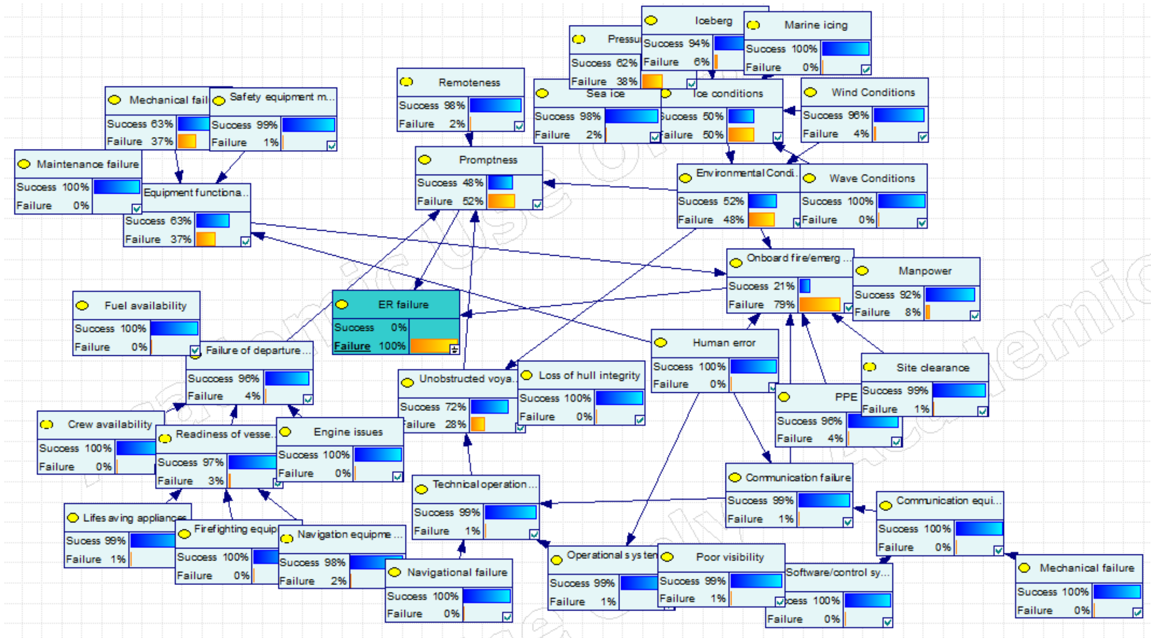


Figure 3.9: BN model is simulated using GeNIe as the probability of ER failure is 1.0.

The ratio of prior and posterior probabilities of the primary events are presented in Table 3.3. The most sensitive change ratio is human error. Mechanical failure, fuel availability, crew availability, lifesaving appliances, firefighting equipment, navigation equipment, hull integrity and navigational failure have similar sensitivity ratio. Other factors do not reflect any significant change when compared with each other.

Table 3.3: The ratio of prior and posterior probabilities of critical factors

Contributing factors	**Prior Probability (Pi)**	**Posterior Probability (Pp)**	**Ratio (Pp/Pi)**
Fuel availability	0.000397	0.003386	8.5280
Crew availability	0.000397	0.003386	8.5280
Lifesaving appliances	0.001	0.008528	8.5280
Firefighting equipment	0.000397	0.003386	8.5280
Navigation equipment	0.00255	0.021747	8.5280
Engine issues	0.00026	0.002217	8.5280
Wind conditions	0.006	0.041225	6.8708
Wave conditions	0.000197	0.001357	6.8865
Sea ice	0.00275	0.017658	6.4211
Pressured ice	0.0594	0.381416	6.4211
Iceberg	0.01	0.064211	6.4211
Marine icing	0.00015	0.000963	6.4211
Loss of hull integrity	0.000133	0.001134	8.5280
Poor visibility	0.0007	0.005442	7.7748
Navigational failure	0.000002	0.000017	8.5280
Human error	**0.0003**	**0.003510**	**11.6989**
Maintenance failure	0.0001	0.000646	6.4551
Mechanical failure	0.0546	0.367678	6.7340
Safety equipment maintenance	0.001	0.006454	6.4539
Remoteness	0.003	0.023331	7.7769
Mechanical failure (Communication)	0.00001	0.000087	8.6550
Software/control system failure	0.0004	0.003282	8.2041
PPE	0.005	0.037295	7.4589
Manpower	0.01	0.078700	7.8700
Site Clearance	0.001	0.007049	7.0494

In this section, the main phases of logistics operations are considered to analyze the risk reduction worth, where evidence is set up as 100% success for each main phase and the probability improvement of logistics failure is estimated as percentage (Table 3.4). It is seen that the most critical phases of logistics operation are: (1) Promptness or vessel reaching the site on time and (2) On-site operation. Promptness depends on the distance of the site, vessel readiness, uninterrupted vessel transit and existing physical environments. The focus should be given to overcome the challenges of logistics operation associated with remoteness and onboard operations.

Table 3.4: Sensitivity of the main phases of logistics operation

ER failure after setting an intermediate event not occurring	**Prior Probability (Pi)**	**Posterior Probability (Pp)**	**Change ratio in percentage ((Pp - Pi)/Pi ×100)**
ER Failure | Departure_Readiness	0.0848	0.0816	3.78
ER Failure | Unobstructed_Voyage		0.0631	25.53
ER Failure | Equipment_Funtionality		0.0560	33.91
ER Failure | Promptness		0.0432	49.08
ER Failure | Onboard_Operation		0.0196	76.91

3.4 Risk Management Strategies

3.4.1 Identification of Safety Measures

After analyzing the contributing factors, possible safety measures are identified that reduce the risk of logistics failure. If there are multiple solutions for a single factor, the safety measures are categorized first according to the risk management principles. It needs an organized approach to take both the effects and costs of each safety measures into account, and thus to achieve an optimal risk management strategy. A safety measure has an effect either on the probabilities of the primary events or the potential consequences. Figure 3.10 illustrates some possible measures that can be applied during the major stages of marine logistics operation. Different types of safety measures exhibit different characteristics, which are classified in Table 3.5. For instance, an inherent safety measure can be such that a vessel is designed and built to withstand in harsh operating conditions. Engineered measures i.e. innovative design, offshore refuge, additional inventory for logistics etc., need additional equipment or installations. For a safety measure that requires additional installation, the fixed cost might be much higher than the operating cost. Procedural measures such as inspection, maintenance or training involve regular operating costs.

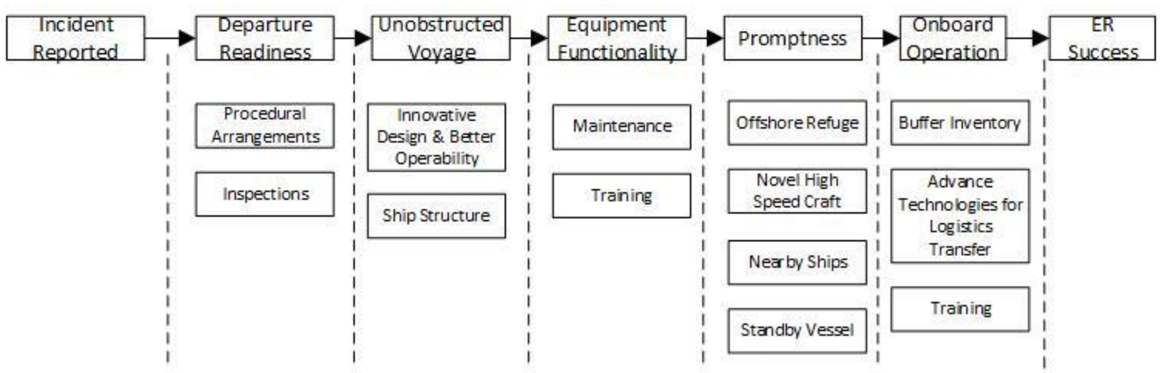


Figure 3.10: Risk reduction measures for different phases of marine logistics operation

Table 3.5: Summary of safety measures in the context of ER failure

Intermediate Events	**Safety Measures**	**Inherent Safety Measures**	**Engineered**	**Procedural**
Failure of departure readiness	Procedural arrangements			×
	Inspection			×
Failure of unobstructed voyage	Innovative design & better operability		×	
	Ship structure	×		
Equipment functionality failure	Maintenance			×
	Training			×
Failure due to delayed response	Offshore refuge		×	
	Novel high-speed craft		×	
	Nearby ships			×
	Standby vessel			×
Onboard operational failure	Buffer inventory		×	
	Advance technologies for logistics transfer		×	
	Training			×

The sensitivity analysis reveals that the most critical phases of logistics operation are promptness and onboard operation. In this study, the emphasis is to overcome the challenges with remoteness and onboard operations. Several alternative solutions are identified, which are described below:

1. *Offshore temporary refuge/hotel:* The concept is to have a temporary hotel in a nearby offshore installation which can facilitate logistics support when a plant is at risk. It is different from the temporary refuge, which is located inside the production plant (Section 3 of ISO 19906). Muster stations are located within a temporary refuge where personnel assemble for evacuation. This temporary refuge/hotel could be a floating structure with a suitable mooring system. It should have all the necessary logistics of a supply vessel including trained personnel who can provide support to restore plants' production and conduct rescue operation when the plant needs to be abandoned. An appropriate vessel suitable for this purpose would be required for transportation between the hotel and plant. A single offshore hotel can provide logistics to more than one offshore production plants if these are situated in close vicinity. The feasibility of such installation, and its conceptual design standards and performance benchmarks will be studied in a future work.

2. *High speed craft/emergency response vessel (ERV):* The ERV should be capable of performing all emergency response support duties relevant to the assessed needs of the offshore facilities, its personnel and the environment. The ERV location should ensure that it is able to transit and respond to the specific emergency within the pre-determined maximum time period relating to the emergency. It should be capable of functioning under all possible environmental conditions and installation hazards to satisfy the facility's requirements in relation

to its emergency response plan. The performance standards for the Emergency Response Vessel in remote harsh environment is presented in Barents 2020: RN04, Final Report, Phase 4.

3. *Standby Vessel:* The Canada-Nova Scotia Offshore Petroleum Board and the Canada-Newfoundland and Labrador Offshore Petroleum Board (the Boards) have issued guidelines to assist operators to achieve compliance with the Drilling and Production Regulations (the Regulations) respecting the suitability and capability of support craft as a standby vessel (SBV) to supply emergency services (Atlantic Canada Standby Vessel (AC-SBV) Guidelines: ISBN: 978-0-994-0857-0-2). Standby vessels are designed, constructed and maintained to operate safely and supply the necessary emergency services in the foreseeable physical environmental conditions prevailing within the area of operations.

4. *Nearby Ships:* Ships near the offshore platform i.e. patrol vessels can be a secondary means of support if others are not available. The presence of a nearby ship that can provide support during the plants' emergencies is uncertain; this should be considered in the risk analysis.

5. *Buffer Inventory:* An alternative approach for the solution of logistics problem that the production facility is designed with buffer inventory. This could be an

additional safety barrier for the plant. A conceptual design, performance standards and its feasibility need to be studied in detail.

3.4.2 Safety Measures Allocation to the Model

In Figure 3.11, the BN model for marine logistics operation incorporates the identified safety features, which are marked as green nodes. There are several alternative safety measures possible, which are presented with purple nodes.

Figure 3.11: Safety measures allocation to the BN model.

The impacts of a safety measure on the likelihood of an undesired event can be derived using the law of total probability. For example, if appropriate training is provided to improve human performance that can eliminate human error, then the probability of human error, $P(HE)$ can be calculated using equation 3.9 (Dianous and Fievez, 2006; Yuan et al., 2013).

$$P(HE) = P(HE|SM_{HE}) \times P(SM_{HE}) + P(HE|\overline{SM_{HE}}) \times P(\overline{SM_{HE}}), \tag{3.9}$$

In the above equation, $P(SM_{HE})$ is the failure probability of training activities; $P(HE|SM_{HE})$ refers to the conditional probability of human error given that the training has failed. Similarly, $P(HE|\overline{SM_{HE}})$ is the conditional probability of human error given that the training is effective. A sample calculation is shown in Figure 3.12 and a comparison of the probabilities with and without safety measures is presented in Table 3.6.

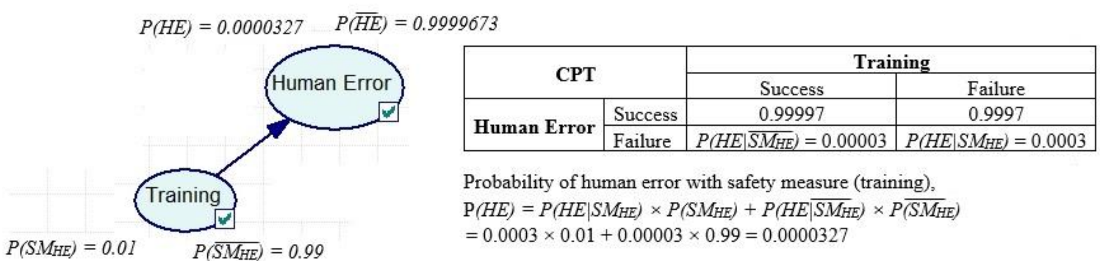


Figure 3.12: Example of updated failure probability calculation with safety measure

Table 3.6: Comparison of probabilities with and without safety measures

Critical Factors	**Safety Measures**	**Alternate Safety Measures**	**Probability without safety measures**	**Probability with safety measures**
Fuel availability	Procedural arrangements		3.97E-04	9.61E-05
Crew availability	Procedural arrangements		3.97E-04	1.06E-04
Readiness of vessel safety equipment		Procedural arrangements	3.94E-03	9.61E-04
		Inspection	3.94E-03	1.02E-03
Engine issues	Inspection		2.60E-04	3.23E-05
Loss of hull integrity	Ship structure		1.33E-04	2.11E-05
Unobstructed voyage failure	Innovative and better operability		2.69E-02	3.24E-03
Maintenance failure	Inspection and maintenance		1.00E-04	1.09E-05
Mechanical failure	Inspection and maintenance		5.46E-02	6.49E-03
Safety equipment maintenance	Inspection and maintenance		1.00E-03	2.08E-04
Human error	Training		3.00E-04	3.27E-05
Promptness		Offshore refuge	5.17E-02	5.17E-04
		Novel high speed craft	5.17E-02	9.67E-03
		Nearby ships	5.17E-02	2.37E-02
		Standby vessel	5.17E-02	1.01E-02
Onboard fire/emergency response failure		Buffer inventory	7.70E-02	3.05E-02
	Advance technologies for logistics transfer		7.70E-02	5.72E-03

To estimate the complete risk value of ER failure, a consequence model should be considered. Consequence models help to calculate the potential damage resulting from the logistics failure along with the probability of the outcomes. The study presents a scenario where an accident has already occurred, and an emergency support has been requested. The failure of emergency response means the onboard personnel need to evacuate the platform if the accident cannot be controlled. Therefore, the consequences of ER failure are categorized into the following:

i. Accident: Onboard personnel managed to escape from the accident site and evacuated successfully.
ii. Major Accident: Onboard personnel managed to escape from the accident site but failed to evacuate the platform.
iii. Catastrophic: Onboard personnel failed to escape from the accident site.

The crew need to assemble at the muster station to evacuate the platform. Evacuation would not be possible if escape failed. The complete risk model is presented in Figure 3.10. The failure probabilities of escape and evacuation in offshore platform accidents are taken as 0.08 and 0.1, respectively (Ping et al., 2017). The consequence severity matrix for this study is presented in Table 3.7 (adapted from Kalantarnia, 2009).

Table 3.7: Consequence types

Consequence	Dollar value equivalent (Million)	Asset loss	Human loss	Environment loss	Reputation
Accident	0.5-50 M	Loss of major portion of equipment/ product	Multiple major injuries, potential disabilities, potential threat to life, or one fatality	Minor offsite impact	Local media coverage or regional media coverage, brief national media note
Major accident	50-100 M	Loss of all equipment/ product	Multiple fatalities	Community advisory	National media coverage, brief note on international media
Catastrophic	> 100 M	Loss of all equipment/ product	More fatalities than type A since personnel could not escape from accident site	Community advisory	National media coverage, brief note on international media

Risk due to logistics failure before and after the application of safety measures is calculated using equation 3.5, which is presented in Table 3.8. The method is illustrated for five alternative safety measures. For example, the risk without any safety measures can be calculated as: $Risk = \sum_{i=1}^{n} P_i \times L_i$ = 1.46E-02 × 25 Million + 6.79E-03 × 75 Million + 6.79E-04 × 75 Million = 0.96 Million. Subsequently, the percentage of risk reduction of each safety measure is calculated using equation 3.6 i.e. *%RR* of offshore refuge can be calculated as: *%RR (Offshore refuge)* = (0.96 – 0.70)/0.96 × 100 = 26.99%. The corresponding *%RR* values of the safety measures are plotted in Figure 3.13, which shows that buffer inventory and offshore refuge have the highest *%RR* values among these five measures. About 30% of risk can be reduced if a nearby offshore refuge or a buffer inventory adjacent to the platform is used, which addresses the challenge of prompt response. An additional advantage of offshore refuge over buffer inventory is that a single installation can support more than one offshore platform in case these are in a close proximity. Also, effective training of emergency crew and onboard personnel, improving the reliability of logistics equipment, innovative technologies suitable for cold weather conditions can significantly reduce onboard operational challenges. Hence, the combination of these measures can be considered in the decision making process for the offshore logistics risk management.

Table 3.8: Risk of ER failure with and without safety measures

Consequences type	Probability before safety measures	Probability after the application of alternative safety measures					Potential losses in Millions (M) of dollars
		Offshore refuge	Novel high speed craft	Nearby ships	Standby vessel	Buffer inventory	
ER failure	8.49E-02	6.53E-02	6.80E-02	7.73E-02	6.83E-02	5.98E-02	-
Accident	1.46E-02	1.07E-02	1.17E-02	1.33E-02	1.17E-02	1.03E-02	25M
Major accident	6.79E-03	4.96E-03	5.44E-03	6.18E-03	5.46E-03	4.78E-03	75M
Catastrophic	6.79E-04	4.96E-04	5.44E-04	6.18E-04	5.46E-04	4.78E-04	120M
Overall risk	0.96M	0.70M	0.77M	0.87M	0.77M	0.67M	-

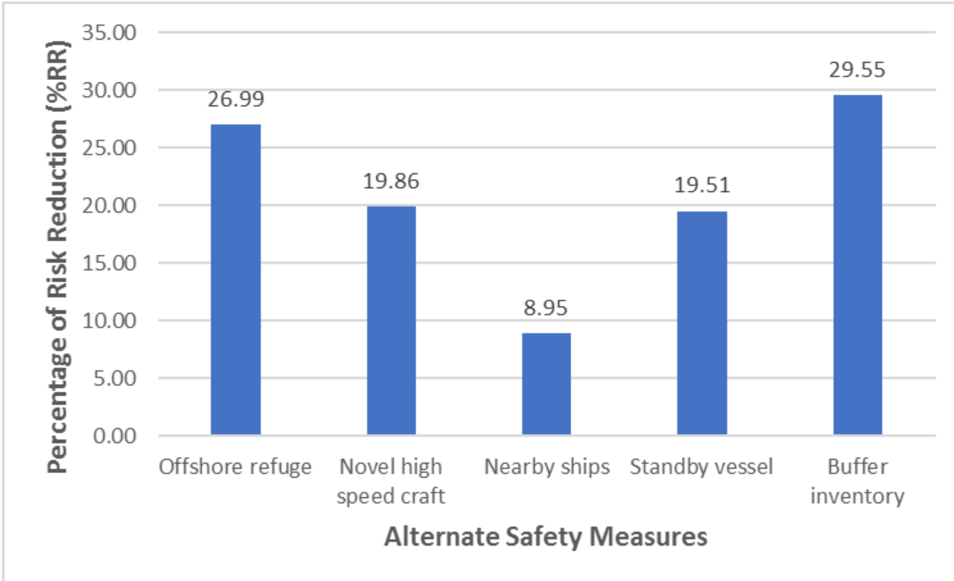


Figure 3.13: Percentage of risk reduction after the application of safety measures

In this case study, the occurrence probability of each consequence is estimated based on the conditional probability data from two experts which are aggregated by the DS rule of combination. This approach may address the uncertainty due to expert knowledge elicitation from multiple sources where a range of occurrence probability of events can be obtained. The ignorance and belief of experts' knowledge are defined based on the basic event probability assignments and the DS rule of combination provides a lower bound and an upper bound of event probabilities which are also referred as belief and plausibility, respectively. Figure 3.14 shows the lower and the upper bounds of each consequence in logistics operation failure, which are calculated using the model based on the aggregated data from both experts.

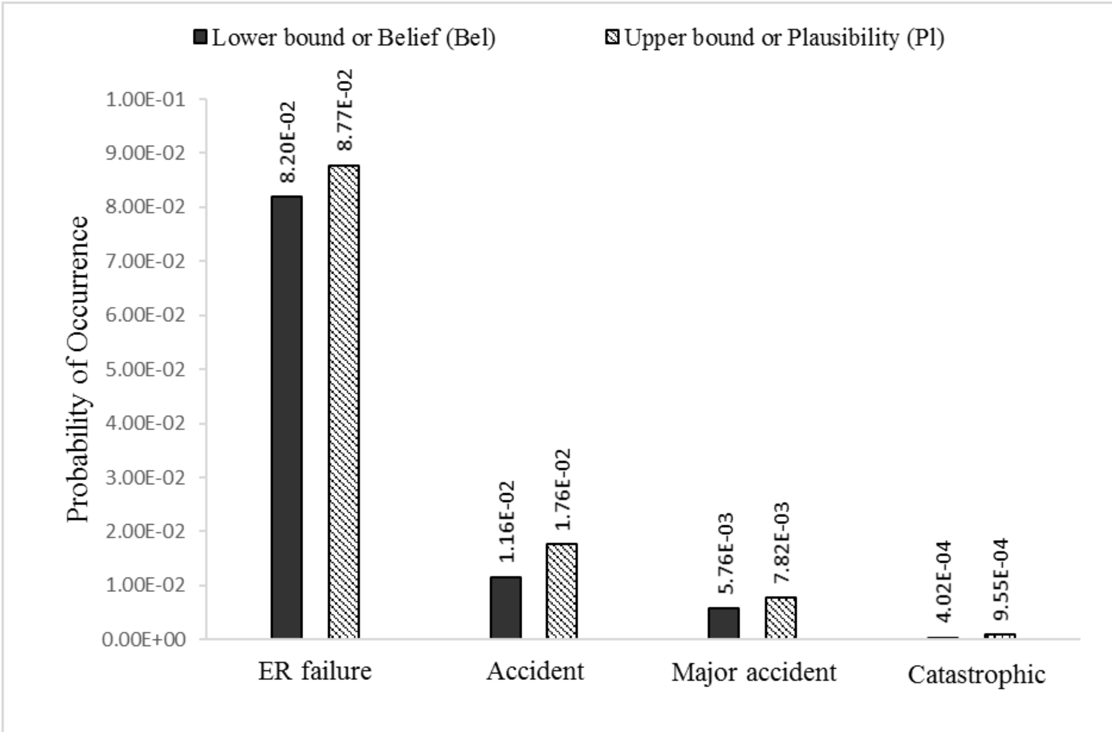


Figure 3.14: Belief structure of consequences

The Bayesian approach is implemented in this study to describe the dependencies among the parameters of offshore logistics operational failure and the probabilistic assessment of possible safety measures in risk reduction. The objective of this case study is to demonstrate the application of the approach, which could be further tested and applied for similar scenarios. Precise outcome can be obtained through further experimentation and validation using more data from subject matter experts. Also, an alternative approach to perform this analysis could be the use of influence diagrams (ID). An ID is a graphical tool that can be used for mapping probabilistic dependencies among the variables in a decision analysis (Howard and Matheson, 1984). Since the risk analysis of logistics failure involves uncertainty and decision-making steps, the applicability of ID within this problem can be further investigated. A simple ID is presented in Figure 3.15. Two elliptical chance variables are risk due to ER failure and cost. The rectangular decision variable indicates the possible safety measures or actions could be taken by the decision makers or stakeholders. These action variables may affect the belief or probability of risk and cost. The rounded rectangle represents a deterministic function to estimate the reduction of risk, which is the function of measured risk and action taken. The hexagonal node represents the risk reduction worth, which is a measure of value or satisfaction with possible outcomes with respect to various actions taken.

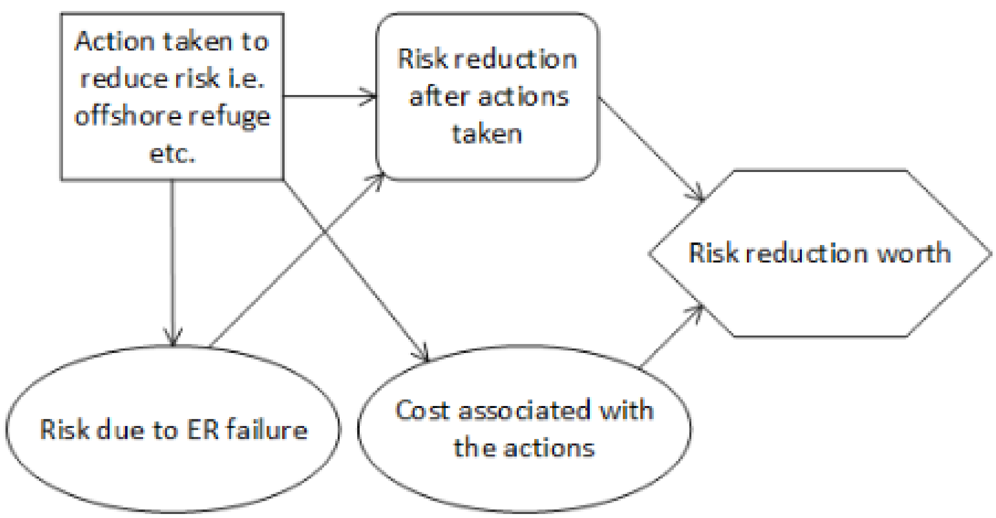


Figure 3.15: An influence diagram for decision making in the risk management of offshore logistics support in a remote harsh environment

3.5 Conclusions

This paper presents a risk model to analyze operational challenges of marine logistics support in harsh environments and proposes risk management strategies to reduce risk. An advanced Bayesian approach is used to address the interdependencies and conditional relationships among the critical factors. The main contribution of this paper is summarized below:

1. The inherent limitations of primary BN model for marine logistics risk are identified by analyzing the network's outcomes. An advanced BN model addressed the interdependencies of contributing factors and the casual relationships are well-defined based on experts' knowledge.
2. A case study is presented to illustrate the logistics risk model. Prior probabilities used in the analysis are based on historical data from literature survey and domain experts. Evidence-based theory is implemented to combine the data from two experts.
3. Sensitivity analysis reveals that the most critical phases of this particular scenario are promptness of response and onboard operation.
4. Safety measures to control and mitigate the marine logistics failure are identified and integrated with the risk model to estimate the reduction of risk. Risk management strategies are developed that emphasize the challenges associated with promptness and onboard operation.

5. Several alternative solutions are considered in the analysis as an effort to find the optimal measures. The concept of offshore temporary refuge or a buffer inventory within the platform can be very promising solutions for the logistics problem in a remote harsh environment.

The economic aspects of these safety measures need to be studied further. Also, discrete probabilities are used in this study. More robust estimation can be obtained if time sensitive data can be used i.e. seasonal probability values. In this study, human error is considered as one parameter, which could be a combination of a series of nodes that would represent different modes of human related failure. With a more detail literature review and practical datasets, the accuracy of this outcome can be further improved. Scarcity of the relevant data is a big challenge for this study. To address the data limitation, integration of the fuzzy theory with the existing Bayesian model could be a promising approach.

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4. Conceptual Development of an Offshore Resource Centre in Support of Remote Harsh Environment Operations

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Co-authorship statement

A version of this manuscript is published in Ocean Engineering. Along with the co-authors, Bruce Colbourne and Faisal Khan, the lead author Md Samsur Rahman formulated the design criteria and developed the concept. Md Samsur Rahman developed the methodology, performed analysis, investigation, prepared original draft and revised the manuscript based on the co-authors' feedback and also the peer review process. Bruce Colbourne supervised and contributed in developing the methodology, formal analysis, writing - review & editing. Faisal Khan supervised and helped in developing the methodology, writing - review & editing, project administration, funding acquisition.

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Abstract

The design and operational planning of an offshore installation must consider environmental challenges along with additional difficulties that arise due to remoteness.

Among the major operational issues, logistics support during routine operations and emergencies is critical. The logistics support from an onshore base to a remote and harsh environment offshore production facility is not sufficiently reliable and quick. In this study, the concept of an intermediate offshore resource centre (ORC) as a potential solution to the logistics problem is presented. The purpose, functional requirements and the conceptual design of an ORC with an illustrative example are discussed. A modular volume-limited ship design concept is adopted here to determine the principal particulars of the ORC in the concept design phase. The required functional elements of the ORC are identified, and then the physical space required for each element is represented graphically as a scaled block with the required volume. The principal dimensions are determined after arranging these functional blocks within a ship-shaped envelope. Finally, the concept design of the vessel system is tested and validated with an analysis of the vessel stability and mooring requirements.

Keywords: Offshore resource centre; remote operation; emergency management, offshore logistic; harsh environment; offshore risk analysis.

4.1 Introduction

Extraction of hydrocarbon in northern offshore regions poses significant challenges due to extreme physical environmental conditions (Hamilton, 2011; Khan et al., 2014; Meling, 2013; Necci et al., 2019). In addition to the environmental challenge, regular logistics support and emergency response become more and more difficult for remote platforms. Long-distance operation of helicopters is particularly risky (Nascimento et al., 2015; Oil & Gas UK, 2013a). Also, the use of a helicopter is limited when weather is not favorable. The idea of an intermediate offshore resource centre (ORC) originated when considering these issues. In previous studies (Rahman et al., 2020, 2019) the logistical challenges of remote offshore operations are identified. These papers present a probabilistic risk analysis using the fault tree (Rahman et al., 2019) and the Bayesian network (Rahman et al., 2020) that essentially estimated the risk of logistics support operation failure in a remote harsh environment. In the main, these risks are shown to be most significantly associated with the distance from shore-based support, particularly the extended flying distance for helicopter based supply and crew transfer. Additional risk of logistics failure is associated with the difficulty in providing timely emergency response and in mobilizing shore-based equipment and assets in response to a remote offshore incident. One practical solution to mitigate both these risks is to provide an intermediate platform or vessel that allows aircraft an intermediate landing/refueling location and at the same time provides a forward staging point for emergency response equipment.

In the current study, the space requirement and thus the overall dimensions of the ORC are estimated to meet the functional requirements for logistics supply to single remote platform. However, the concept and the approach remain the same for supporting multiple oil field operations. The space requirement to support multiple platforms can be determined using the same approach to that presented in this study. Thus the concept remains the same but the size may increase. Such a platform probably becomes more and more economically efficient as it services a greater number of offshore installations.

An ORC reduces the risk for daily operations in addition to providing a forward base for emergency response. Thus, the ORC has two primary mission requirements for cases where an offshore development is exceptionally remote from land-based support:

- Provide an intermediate point for helicopter operations that enables refueling, alternate landing and shorter transit distance.
- Provide a forward staging or response asset for emergency response in case of fire, spill, sinking or ice damage.

This study is part of a larger research project aimed at identifying risks and risk reduction measures, including the economic costs and benefits of the risk reduction measures, with a particular emphasis on remote offshore operations in harsh environments. The objective of this component of the larger study is to develop one particular risk reduction measure which addresses the most significant risks identified in earlier parts of the study.

The concept of an intermediate offshore base for various logistics support is not entirely new. The US military studied the idea of a mobile offshore base (MOB) for helicopter and fixed-wing cargo aircraft operation, maintenance and other military logistical supports. The mission requirements for fixed wing aircraft needed a very large floating structure of approximately 1500 m in length. The technical and financial feasibility were both significant concerns associated with such an enormous floating structure (McAllister, 1997; Naval Facilities Engineering Service Center, 2000; Remmers et al., 1998). (Nordbø, 2013) presented mathematical models to study the feasibility of intermediate bulk storage to support multiple remote hydrocarbon production facilities. The concept of such a logistics hub for personnel accommodation is found in (Moyano, 2016; Vilameá et al., 2011). Accommodation vessels and semi-submersibles also referred to as “Floatels” are often used near or together with the production facilities for accommodating offshore workers (Floatel International Group, 2019; Prosafe, 2019; Pérez et al., 2012).

None of the above concepts provide a suitable starting point for the proposed ORC, and thus a concept is developed from basic requirements. The conceptual model of an offshore resource centre starts with defining functional requirements and environmental constraints followed by selection of the type of structure that can be suitable for these requirements. Space requirements are estimated for each of the functional requirements to determine the overall space requirement for the ORC. Figure 4.1 illustrates the basic functional concept of an intermediate distance offshore resource centre (ORC) for logistics support of one or more offshore platforms. In particular, offshore personnel are carried on/off the ORC from the onshore base and the production platform by helicopters (preferable and weather permitted) or marine vessels. The ORC thus needs to be equipped with facilities to accommodate in-transit personnel during their transit hours. A more detailed study would be required to model scheduling of such transfer operations that is not included here. This paper aims to outline the requirements of the ORC platform and provide a conceptual design outline for a moored vessel that meets the identified requirements.

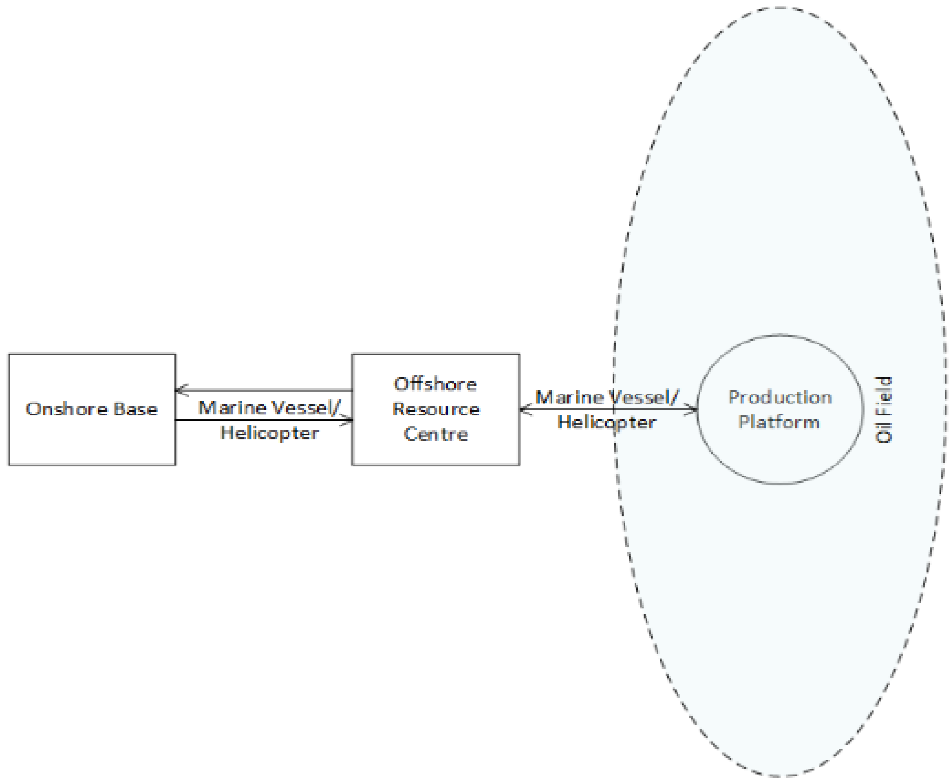

Figure 4.1: A solution for logistics support and emergency response in remote harsh environments

4.2 ORC Performance Requirements

Performance requirements for the ORC stem from the previous risk analysis (Rahman et al., 2020, 2019) and from the operating environment. The risk reduction objectives for the platforms are to reduce the effective flying distance to the production platform, and to provide more timely emergency response. These objectives are largely independent of operating location and are covered in more detail in the following section. Environmental conditions are location specific and in the present study we have chosen the North West Atlantic as an illustrative operational scenario. This environment presents a number of challenges. This choice is also driven by current consideration of a remote location for offshore oil production.

4.2.1 Risk reduction objectives

The main operational function of the ORC is to serve as a helicopter intermediate landing point. This function requires that the ORC be positioned at a fixed location to provide an intermediate stopping point for regularly scheduled helicopter operations to and from the remote production facility. This would incorporate the ability to land and refuel two helicopters simultaneously and potentially provide service to one. The concept of an ORC as a mid-way stopping point for one or more remote platforms means that it is entirely likely that one helicopter would be inbound while another is outbound. Furthermore, in the case of emergency it would be advantageous to be able to operate two transports and have some redundancy in the system.

As part of the role of intermediate landing point, the ORC would also provide temporary accommodation with required amenities for in-transit offshore personnel. This will be used as a station for the personnel of the production platform on their way to/from the production installation.

The final regular function of the ORC would be to provide local and regional communications with the production facilities, nearby vessels and other installations in the vicinity, rescue craft and coast stations.

The second primary function of the ORC is as an emergency response centre. In this mode the ORC would respond to emergency incidents such as fire, explosions, leak, spills, human or weather-induced damages, equipment failure, etc. Response equipment, particularly for spill containment would be stored on board the ORC to speed reaction to offshore incidents by supply and standby vessels. The ORC would also provide, in case of platform abandonment, the capacity to accommodate evacuated personnel in emergency conditions. This would include the ability to deal with casualties.

A possible scenario is considered to be that the ORC moves temporarily closer to the location of a disaster while standby and other vessels deal with the actual events using equipment and supplies drawn from that stored on the ORC. This may be augmented by transferring an emergency logistics support team to respond to an incident, from the shore base to the ORC. However, this mode of response may not be optimum if it limits flight operations by increasing the flying distance to the ORC. Rather than preclude this response possibility at this concept stage, the system is conceived to provide the ability to move off station for emergency response. In either mode of response – on or off station – the ORC is configured to acts as a local command centre for emergency response.

Hence, the performance requirements of the ORC can be summarized as:

- Maintain position at a fixed location with an ability to move.
- Provide a base for helicopter landing, refueling and service.
- Provide short term in-transit accommodation for regular passengers.
- Have the ability to move off station in the event of emergency.
- Provide short term accommodation for emergency responders.
- Provide forward storage and distribution of emergency response equipment and supplies
- Accommodate personnel from the production platform in case of evacuation.
- Provide medical facilities for emergency treatment.
- Provide local and regional communications with the production facilities, nearby vessels and other installations in the vicinity, rescue craft and coast stations.
- Act as an incident command centre for emergency response.

4.2.2 Environmental Conditions

The Flemish Pass Basin is chosen for a case study to illustrate the concept design development of the ORC. Although some aspects of an ORC are site independent, other aspects would be dependent on location. Thus the basic functions are dictated by the distance of the supported platform from shore, but environmental conditions are site specific and thus it is necessary to have an example location to fully develop the concept. Other locations would maintain the basic concept and concept development process but exhibit different characteristics based on the requirements of the specific location.

The Flemish Pass basin is located approximately 480 km east of St. John's, Newfoundland and Labrador. Equinor Canada Ltd. (Equinor) is proposing to conduct an exploration drilling project in the Flemish Pass Basin between 2019 and 2027 (Canada Impact Assessment Act, 2019). In this study, the proposed ORC would be located at an intermediate location between the shore (St. John's) base and the drilling sites. Although the Flemish Pass is a deep water location at the edge of the continental shelf, the ORC is likely to be located on the Grand Banks, which is part of the continental shelf, as that is the intermediate location – see Figure 4.2.

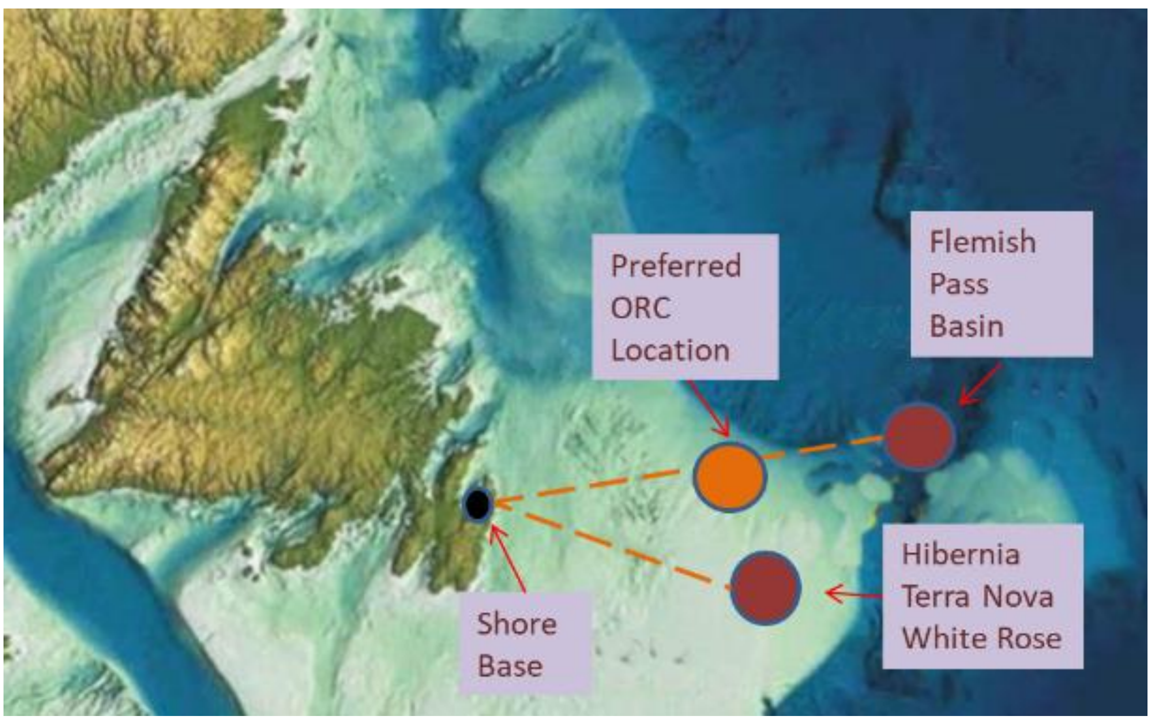

Figure 4.2: The possible location of the ORC offshore Newfoundland

This example location is immediately relevant as the region is in the early stages of consideration for development and the distance from land is likely to be the most challenging aspect of the development. This provides a real-life example that fits the ORC concept. In addition, this region lacks the density of existing offshore installations that can provide mutual support such as would be available in other regions such as the North Sea.

Information about physical environmental conditions off Newfoundland (near the Grand Banks and Flemish Pass regions) is extracted from (ISO 19906, 2010; Nalcor Energy, 2017). These regions are considered to be harsh environments conditions due to the likelihood of intense storms and the presence of seasonal ice (pack ice and icebergs). Ice accretion on marine structures can also occur between December and March because of temperature, wind and wave conditions. During the spring and summer months, poor visibility often occurs due to fog. Restricted visibility may also occur during winter months caused by snow in addition to fog and mist. Representative physical environmental conditions are presented in Table 4.1.

Table 4.1: Physical environmental conditions of Flemish Pass and Grand Banks regions

Parameter	**Classification**	**Flemish Pass**	**Grand Banks**
Water Depth		550-1200	75-125
Wind Speed (m/s)	Mean (Annual)	9.74	9.17
	100 year (Annual)	33.4	32.5
Significant Wave Height (m)	Mean (Annual)	3.23	2.97
	100 year (Annual)	16.3	15.6
Current Velocity (m/s)	Average	0.22	0.18
	100 year extreme value	1.38	1.3
Pack Ice	Annual mean pack ice concentration	4/10-6/10	4/10-6/10
	Floe thickness (m)	0.7-1.2	0.7-1.2
Iceberg	Total Iceberg Counts (open water) between 1998-2012	22	442
	Mean iceberg size (m)	66	85
Harshness Index	Fleming-Drover	2.65	2.27

The harshness index suggests that the Flemish Pass region has more extreme environmental conditions than the Grand Banks which has higher wind speed, wave height, water depth. Although, Data shows that there are fewer icebergs in the Flemish Pass area than Grand Banks. The physical environment of both these areas is considered for the ORC design since it would be operated in both these regions.

4.3 Concept Development

4.3.1 Platform Type

Based on the requirements outlined above, several platform options were evaluated, including a fixed platform, a semi-submersible platform, and a ship-shaped platform. Since one of the functions of the ORC is that it should be able to respond during emergency conditions, it must be a floating structure with a propulsion system. This eliminates the idea of a fixed platform. Although, a semi-submersible has lower motions than a ship-shaped vessel, a ship-shaped vessel is preferable to a semi-submersible in ice conditions although motion stability needs to be considered for determining the principal dimensions of a vessel to ensure crew comfort and safer helicopter operation in expected sea conditions. Furthermore, it is expected that a ship would achieve faster response for emergency support.

4.3.2 Positioning

The ORC is expected to be moored at an intermediate location on the Grand Banks and thus in relatively shallow approximately 75m – 125m water. The vessel may also operate in deep water (550-1200m) and will be subject to high wind and waves. Also, there is a likelihood of the presence of pack ice and icebergs over the operating region. Either dynamic positioning (DP) or anchor mooring can be used for station keeping in this water depth range.

The life cycle cost of a full time DP system is relatively expensive. There are regulatory requirements for system redundancy and equipment space that introduce significant initial cost. In comparison, the initial cost of an anchor mooring system is lower but costs associated with the on-site installation offset some of the lower equipment cost.

The more significant drawback is that during operation, a full time DP system requires continuous fuel supply to keep the system active, which adds to the operating costs in terms of both fuel costs and delivery.

The requirement to minimize vessel motions and mooring loads leads to a preference for a weathervaning system rather than a spread mooring. This led to consideration of a scaled-down turret mooring which would provide the weathervaning capability but did not require the fluid transfer capability fitted in most offshore turret moorings. In a turret mooring system, several mooring legs are attached to a turret that includes bearings to allow the vessel to rotate 360° around the anchor legs. Turret moorings are mostly used for weathervaning monohulled vessels. This enables the vessel to change heading into the dominant weather thus minimizing environmental loads and vessel motions. A turret may be mounted outside the bow or inside the forward half of the vessel hull in an internal turret configuration. The internal configuration is preferable for more severe environments particularly those with ice as the mooring components are protected from ice impact.

A disconnectable version of a turret mooring provides for the stated requirements to move off station in emergencies. Disconnectable versions of the internal turret consist of a submerged spider buoy coupled to the lower portion of the rotating turret and supporting the individual mooring lines. When the buoy is disconnected, it sinks to a predetermined depth and supports the mooring lines above the seabed making reconnection relatively straightforward (Chakrabarti, 2005).

A typical example of a disconnectable internal turret is the Terra Nova FPSO turret system (Duggal et al., 2000). The Terra Nova FPSO operates in similar environmental conditions. The basic ideas of this system can be adopted for the ORC concept. However, the mission and size of the ORC is substantially different from the Terra Nova FPSO and thus the details of the ORC mooring system would be relatively simpler and smaller.

In summary, considering the required functions of the ORC and the example environmental conditions, a full time DP system was judged to be too operationally and environmentally expensive as the positioning system and a passive weathervaning anchor mooring was judged to be preferable.

The possible use of a DP system for mooring assist or for position maintenance when off the mooring is incorporated into the concept but in this case the system is supplementary to the main passive mooring system.

4.3.3 Vessel Development

Having established the basic requirements for a ship shaped platform on a passive weathervaning and disconnectable mooring, the layout of the vessel itself was developed. The ORC has elements of widely varying ship types and there is no single historical basis ship type to start the concept design process. The mission requirements of ORC partially match those of offshore support/standby vessels, accommodation vessels/flotels, and military fleet support ships. The ORC needs much larger capacity than an offshore supply vessel. Accommodation vessels or flotels are specifically designed for passenger accommodation and not designed for emergency support. The ORC has a requirement to accommodate in-transit platform crew, or possibly evacuees, generally for short periods but possibly for longer periods of up to a day or two. Floatels provide longer term accommodation and food service for a similar client group and thus some of the features of floatels were considered in developing the ORC. Fleet replenishment vessels are larger ships used by the military to provide logistics support to combat vessels. These vessels are frequently based on RO-RO vessels due to a requirement to deliver land forces, which is not a mission requirement of the ORC. Since there is exactly no basis ship for ORC, but there are elements of ORC in a number of existing ship types, the concept design is developed using a process where the desired particulars and design features of all these types of ships are used.

4.3.3.1 *Helicopter operation*

The ORC includes two helicopter platforms to meet the functional requirements. Helicopters are used for two purposes depending on weather conditions and the mode of

ORC operation: transporting crews to/from the onshore base and production platform, and emergency support such as search and rescue operations. Since regular helicopter operation would be conducted in two directions, there would be a significant number of inbound and outbound flights to the ORC. In addition, in the situation when one helideck is occupied by a helicopter, then another landing area would be required if another helicopter needs to land. Based on this demand, the ORC would have two full sized helidecks. In addition, there is an expectation that helicopters may need to be serviced or wait out inclement weather so a hangar is fitted to one of the helicopter decks for storage of one (or more) of the helicopters.

The proposed relatively high frequency of helicopter operations requires consideration of a control tower for regional air traffic management and for landing and takeoff control. This space would ideally have visual contact with both of the helicopter decks and so would be located centrally in the vessel either above or just below the bridge deck. This has been incorporated into the concept.

Current operations on the east coast of Canada are generally conducted using Sikorsky S92 Helicopters, a relatively large aircraft with characteristics provided in Table 4.2. Data from Sikorsky S-92 specifications are collected from (Lockheed Martin, 2019).

Table 4.2: General characteristics of Sikorsky S-92

Crew	2 (pilot, co-pilot)
Capacity	19 passengers
Length	20.88 m
Rotor diameter	17.17 m
Height	4.71 m
Empty weight	7,030 kg)
Loaded weight	12,020 kg
Max. takeoff weight	12,568 kg
Fuselage length	17.1 m
Fuselage width	5.26 m
Maximum speed	306 km/h
Cruise speed	280 km/h
Range	1000 km

Dimensioning of the helidecks and hangars is based on this aircraft. Consideration of helideck arrangements are presented in the following:

Ship motion and air turbulence should be minimum for the safe landing of a helicopter. A vessel has relatively lesser motions at the amidships, however, this competes with other systems installed topside, for example, deckhouse, intakes and uptakes (Lamb, 2004). Hence, forward and aft locations are more readily available and provide better approaches for landing and taking off. An aft location is typical for naval ships but helidecks are usually fitted at the fore part or above the wheelhouse in offshore supply vessels. A helideck can be placed at the aft and another at the forepart of the ORC. An advantage of arranging separate helidecks at the fore and aft is a safer design that isolates hazards or accidents on one deck from the other.

Offshore vessels with helicopter refueling systems have special design and construction requirements. Since the ORC would be equipped with a helicopter refueling system, the concept is compliant with existing regulations indicated by the regulatory bodies such as Civil Aviation Authority, classification societies, etc. Hence, the space for Fuel Storage and Refueling Equipment Area, fire safety system, and electrical system is notionally included in the concept but would be detailed during a later design phase.

4.3.3.2 *Emergency Equipment*

As one of the important functional requirements, the ORC would be equipped with emergency response (ER) equipment and supplies and an arrangement for deploying them when required. For the present concept, the ORC would operate as a kind of mothership that would coordinate operations with other vessels during emergencies. Under this scenario the ORC could move to the accident site for ER and work with other available assets or remain on station. In either case the ORC would serve as the command and control centre for the coordinated response. Significant space under the main deck is included to store the equipment and space and crane capacity is provided on the main deck for deployment. In addition, the ORC would have a designated space on the deck to safely recover persons from the water and/or other craft. A list of stored emergency equipment is provided below (CNLOPB, 2018; Oil and Gas, 2013b):

Oil recovery equipment. Space is allocated in the ORC to store recovered oil with a capacity of 10,000-bbl storage.

Survivor rescue equipment. The ORC would be equipped with fast rescue craft (FRC) and Launching Arrangements, survivor retrieval devices, climbing aids, rescue hooks, and lifebuoys to meet the requirements of the LSA Code, Section 2.1.

Firefighting equipment. The design criteria and functional requirements would be adopted from firefighting ships and the guidelines are available in class rules e.g. ABS FFV 1, FFV 2, or FFV 3.

4.3.3.3 *Command Centre*

A specific operational space located above the bridge deck is provided with communications capability and physical layout for the vessel to be a command and control vessel or a primary response vessel.

4.3.4 Layout, dimensions and functional relationships

The required elements of the ship/platform are identified considering the main features above and the more routine aspects of a vessel. The physical size of each element is estimated, based on similar functional spaces in other vessels, offshore platforms or from land based installations. These space/area/volume requirements are represented graphically as a scaled block with the required size. Data for individual functional blocks are drawn from existing examples with the desired functionality, and individually scaled to fit the expected requirement of the ORC. For example, the disconnectable mooring turret dimensions are based on turret systems fitted to Grand Banks FPSOs but scaled down by estimated ship size and reduced by the exclusion of fluid piping and swivels. A graphical example of estimating the dimension of a hospital block is presented in Figure 4.3. The main functional blocks considered in the concept development are illustrated in Figure 4.4.

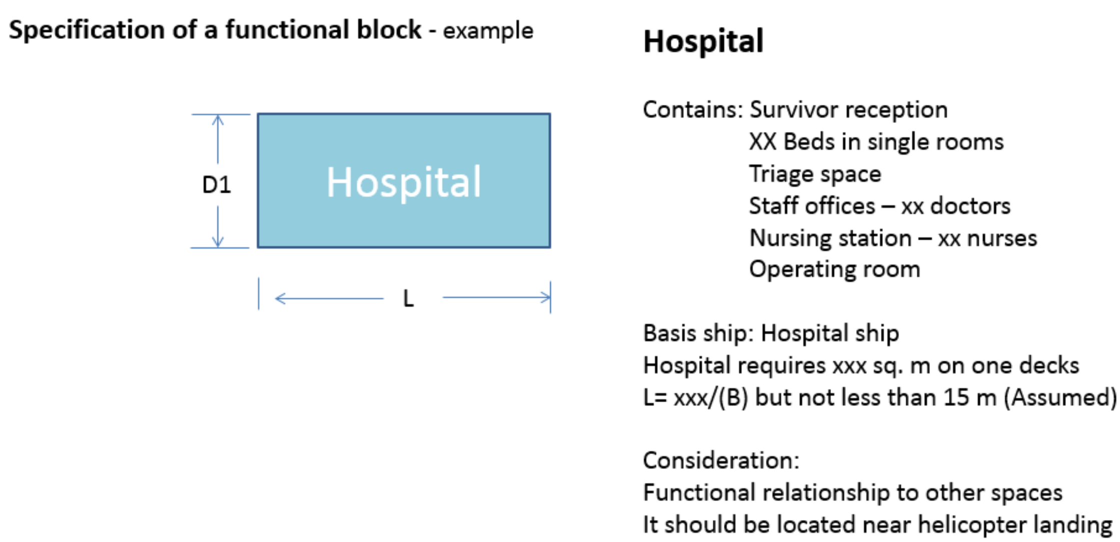

Figure 4.3: An example of estimation the dimension of a functional block

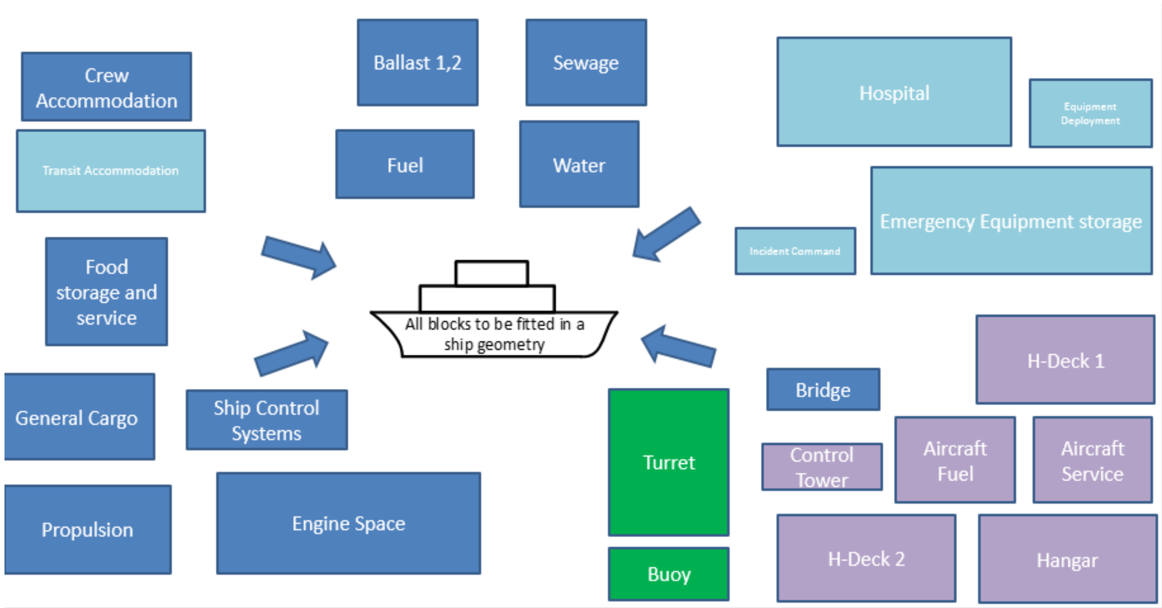

Figure 4.4: Example of functional blocks that requires space

The individual blocks are then logically arranged in terms of functional requirements/relationships and a ship envelope created around the scaled blocks (Figure 4.5). In this way the initial size of the overall ORC vessel is estimated and, where necessary, the size of functional blocks (such as engine, propulsion, fuel, turret) adjusted up or down based on the overall size of the ORC vessel. This in turn lead to refinement of the overall ship envelope, but the process converges much the same way a conventional ship design spiral converges. This is a variation of the design spiral process adapted to allow functional elements to be drawn from different ship types and incorporated into a design with a novel combination of features.

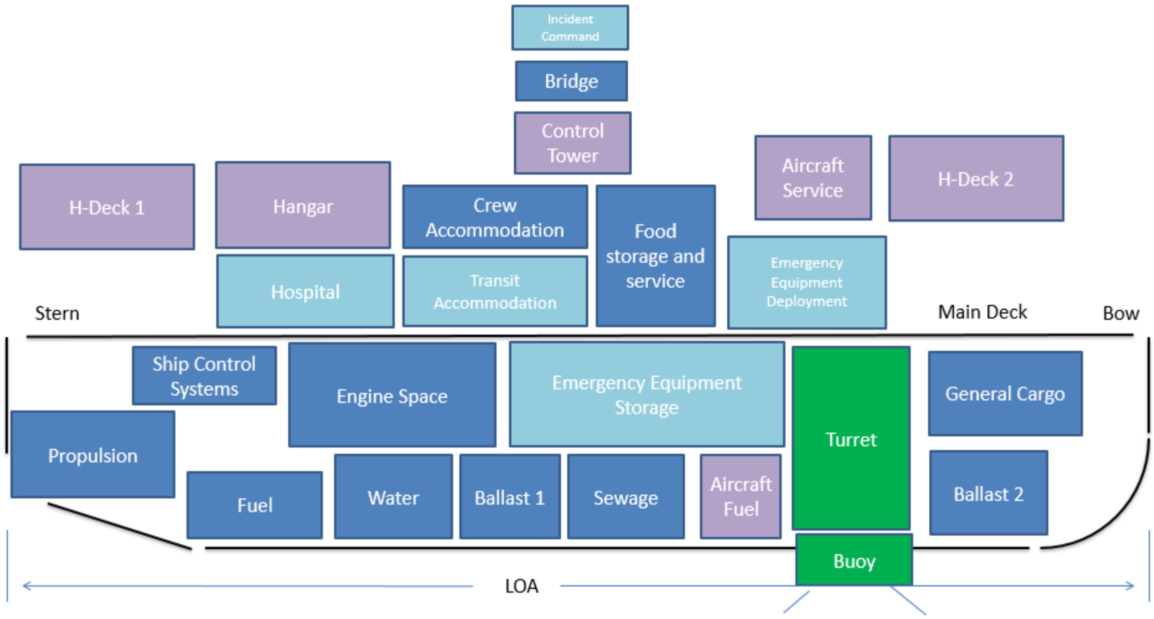

Figure 4.5: Function space blocks arranged within ship envelope

A list of all the functional blocks are provided in Table 4.3. The development of the space requirements for the hospital, mooring system and helicopter operation are described in some detail in the following sections. These three functions were chosen as examples due to their relative importance in the ORC concept. They also illustrate the methods used to adapt functions from other vessels to the ORC concept.

Table 4.3: List of functional blocks

Type	Name of the Block
Accommodation	Transit accommodation
	Crew accommodation
Service	Food storage and service
Medical	Hospital
Tanks and storage	Water
	Sewage
	General cargo
	Store
	Bulk space
	Fuel
	Ballast
	Recovered oil
Mooring	Turret
	Buoy
Helicopter operation	Helideck 1
	Helideck 2
	Hangar
	Aircraft service
	Aircraft fuel
Machinery and engine spaces	Engine space
	Propulsion
	Bow thruster room
	Ship control systems
	Funnel
Emergency Equipment	Emergency equipment storage
	Emergency equipment deployment
Control rooms	Bridge
	Incident command
	Control tower

4.3.4.1 *Hospital*

As a functional requirement, the ORC would have provision for medical support from a medical practitioner at any time. The medical facilities consist of the followings (Norwegian Maritime Medical Centre, 2006):

- A medical unit with pharmacy and medical equipment.
- A treatment room for ill or injured persons.
- One to three medical practitioners who, in cooperation with doctors onshore, will be responsible for medical first aid and medical treatment.
- A designated decontamination space for cleaning survivors upon retrieval and prevent contamination of the ORC's medical or living spaces.
- An enclosed area for survivor reception/triage with access to the accommodations that are designated for registration, distribution of sundries, etc.
- A designated space for storing non-survivors, which should be cool, ventilated and illuminated.

The following elements are considered when locating the ship hospital:

- The ability to carry an injured person on a stretcher from the most likely places of injury to the hospital. The chance of getting an injured person from the production facility is higher than inbound traffic from shore. The distance from the helipad to the hospital facility should be a minimum. There should be easy access for patient ingress/egress from the helideck and rescue zone to the hospital, preferably avoiding stairs/ladders. Also, the location of and angles between corridors and doors are considered.

- Stable enough to carry out any medical procedure if required.
- Sufficient HVAC (including space for the equipment) is provided to regulate internal temperatures of the hospital space.

The area of each function of the hospital is estimated based on a hospital ship, LSD-48, USS Ashland, Whidbey Island-class ship (Carey et al., 2002) and provided in Table 4.4. However, the numbers required are scaled-down as the ORC is not specifically a hospital ship and the capacity requirements are much lower.

Table 4.4: Space for hospital

Hospital				
Category	m^2/pa	Height (m)	Total Area (m^2)	Total Volume (m^3)
Decontamination Area	0.51	3	40	120
Main Laboratory	0.92	3	72	216
Pharmacy	0.31	3	24	72
Intensive care ward (2 beds)	0.24	3	19	57
Survivor Reception/triage area	1.54	3	120	360
Hospital administration (staff office and nursing station)	0.38	3	30	90
General care ward (5 beds)	0.21	3	16	48
Non-Survivors	0.23	3	18	54
TOTAL SPACE FOR HOSPITAL FACILITIES	**4.35**	**m^2/pa**	**339**	**1017**
Functional block length (m)				15.07
Functional block height (m)				3
No of Deck				1

4.3.4.2 *Mooring system*

The use of a disconnectable turret mooring in the ORC is a novel approach as the reduced size, and lack of fluid transfer functions make it somewhat different from existing examples. The space requirement is estimated based on the Terra Nova FPSO mooring system. The Terra Nova FPSO has a disconnectable turret mooring system and this is operated in a similar environmental condition.

The turret position influences the mooring line tensions, weathervaning capability and the arrangement of other design blocks. It is easier to weathervane when the turret is moved further forward from the midship, although the vertical motions will increase and that will increase mooring line tensions. The turret location is chosen between the forward helideck and the accommodation blocks in the midship.

Estimate space for turret. At the early stage of the ORC design, not much information is available and initially assumptions are made. The functional space requirement can be updated as the concept develops. At the beginning of the concept development, the mooring system space is estimated by comparing the size (displacement) of the Terra Nova FPSO and a Royal Canadian Navy joint support ship having a few similar functionalities to the ORC. Table 4.5 provides the turret specification is estimated after a few iterations for the projected ORC displacement. Further details of the Terra Nova FPSO turret system are available in (Duggal et al., 2000).

Table 4.5: ORC turret specification

ORC Mooring (Turret)	Value	Unit
Terra Nova FPSO displacement	193000	Tonne
Estimated volume occupied by Terra Nova FPSO mooring under deck	6380.55	m^3
ORC displacement (Iterations)	14994.64	Tonne
Vessel displacement ratio	0.08	
Estimated volume of occupied by ORC mooring under deck	**495.72**	m^3
Estimated ORC height (Iterations)	10.1	m
Terra Nova FPSO turret keel and deck diameter ratio	1.79	
Projected ORC turret diameter (Deck)	**5.59**	m
Projected ORC turret diameter (Keel)	**10.01**	m

Buoy. Similar to the Terra Nova FPSO, a spider buoy will be connected at the lower portion of the ORC turret. Spaces must be provided for arranging the buoy retrieval system and load transfer mechanism at the lower turret. The displacement ratio of the FPSO and the ORC is similarly used to estimate the buoy specifications.

4.3.4.3 *Helicopter Operation*

Helidecks. There are two helidecks, fore and aft on the ORC. The helidecks require large deck areas and unobstructed approach paths. The spaces are determined based on the type/size of the helicopter that would be landing.

According to (ABS, 2015), a helicopter deck containing a circle must have a minimum diameter equal to the overall length (D or D-value) of the largest helicopter using the helicopter deck. The approach/departure sector must be at least 210° free of obstruction. The required minimum deck lengths for the helidecks are given in Table 4.6.

Table 4.6: Helidecks specifications

Helideck	**Diameter/O.L./D-value (m)**	**Total Area (m^2)**
Deck (D-value)	21	346.36
Obstacle free sector (0.33D)	6.93	173.25
Total Space		519.61
Functional block length (m)		**27.93**

Hangar. The ORC requires a helicopter hangar to support embarked helicopters. The size of the hangar is dictated by the dimensions of the helicopter and clearances for access. There are three basic types of hangars: fixed or telescoping at the landing deck level, and below decks (Lamb, 2004). A fixed hangar is placed adjacent to the aft helideck at the same deck level. The required dimension is determined based on the specification of example helicopter (Sikorsky S92A). The estimated hangar size is given in Table 4.7.

Table 4.7: Hangar specifications

Hanger	Dimension	Total Area (m^2)
Helicopter	D/O.L. = 21m and H = 5.47m	
Allowance	D/O.L. + 1m and H + 0.5m	495
Additional space for helicopter maintenance and access to hospital		22.5
Total Space		517.50
Functional block length (m)		**23**
Functional block height (m)		**5.97**

4.3.5 Arrangement of Functional Blocks and Overall Sizing

After determining all the functional block dimensions using the methodology above, the blocks are arranged in a ship-shaped envelope. When arranging these blocks, the following relationships are considered:

- Accommodation and hospital spaces are located above the main deck in a deckhouse to minimize noise and ensure habitability and safety according to the International Labor Organization (ILO) Regulations on Crew Accommodation and International Convention for Safety of Life (SOLAS).
- Helipad and hangar are adjacent and located at the same level.
- Hospital is located close to the helideck for easy access.

- Tanks and other heavier items are placed on lower decks within the hull.
- The ORC length is dictated by required functional deck lengths where the helidecks, hangar, accommodation block, mooring, emergency response equipment need to be placed.
- Bridge, command centre and control tower are located such that visual obstructions are minimized.
- Helidecks are placed such that enough clearance is provided to mitigate effects from shipped green water or wave spray.
- Emergency equipment storage is located below the emergency equipment deployment area to ensure that these are easily accessible.
- The breadth of the ORC is dictated by the helideck specification and vessel stability requirements.

Based on these considerations, several iterations were performed, moving from the functional block diagram of Figure 4.5 to the concept general arrangement for the proposed ORC presented in Figure 4.6 and Figure 4.7. The estimated dimensions resulting from this assembly are overall length: 159.63 m, breadth: 22.50 m, design draft: 5.80 m.

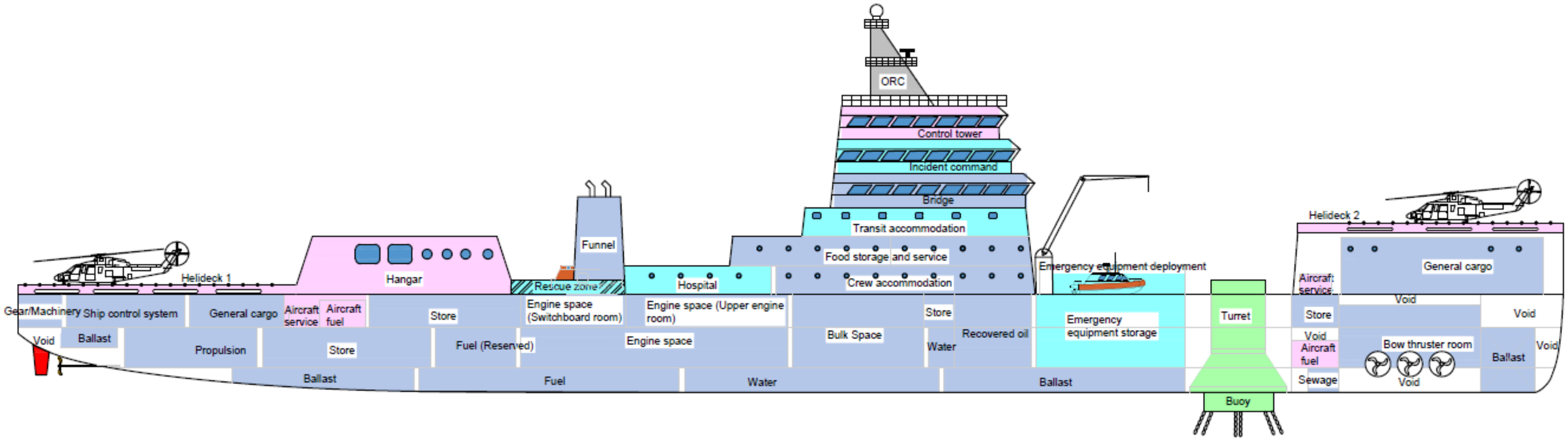

Figure 4.6: The proposed ORC profile to illustrate the arrangement of all functional blocks

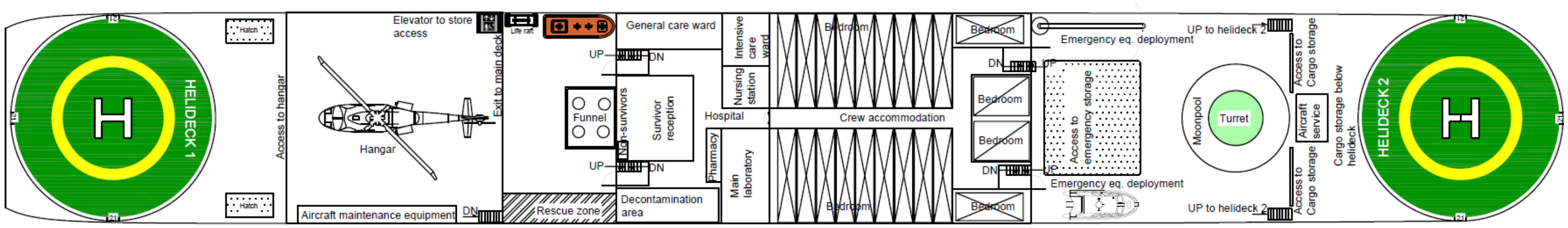

Figure 4.7: Main deck layout

4.4 Validation of Concept

Two preliminary analyses were conducted to validate the ORC concept. These were the vessel stability and an analysis of the mooring loads. Stability analysis was performed to ensure that the dimensions of the vessel, as derived from the assembly of functional blocks, would provide a vessel concept with reasonable form and stability characteristics. This is a practical check on the dimensions of the overall vessel. The mooring analysis was performed to provide a check on the initial mooring dimensions derived from the functional block estimate for the mooring system. The platform development is an iterative process and these analyses provide the next iteration on the initial scoping provided by the functional block process. With the completion of these two analyses, the concept is validated as a credible platform concept that answers the requirements developed from the originally referenced risk analysis. Further refinement would be possible in later stages without changing the basic ideas embodied in the concept.

4.4.1 Vessel Stability

The intact stability criteria are typically evaluated early in a ship development process as principal dimensions are strongly influenced by stability criteria. The ORC platform should be compliant with general intact stability criteria for ships (IMO, 2008):

“

- The area under the righting lever curve (GZ curve) shall not be less than 0.055 metre-radians up to $\theta = 30°$ angle of heel and not less than 0.09 metre-radians up to $\theta = 40°$ or the angle of flooding θ_f if this angle is less than 40°. Additionally, the area under the righting lever curve between the angles of heel of 30° and 40° or between 30° and θ_f, if this angle is less than 40°, shall not be less than 0.03 metre-radians.

- The righting lever (GZ) shall be at least 0.20 m at an angle of heel equal to or greater than 30°.
- The maximum righting lever should occur at an angle of heel preferably exceeding 30° but not less than 25°.
- The initial metacentric height, GM_0 shall not be less than 0.15 m."

Several additional criteria should be satisfied:

- Vessel specific rules i.e. offshore service vessel (IMO, 2008), standby vessel (DNV GL, 2015).
- Severe wind and rolling criterion (weather criterion) considering the operating environment of the ORC (IMO, 2008).
- Icing considerations (IMO, 2008).

Although many of the normal inputs such as the loading conditions, weights and positions of all items, bulkhead arrangements, etc. are not firm at this stage, estimates for cg and weight distribution are based on similar sized and function vessels. Using the particulars developed in the concept design, a 3D hull model is generated. The initial hydrostatic particulars are presented in Figure 4.8.

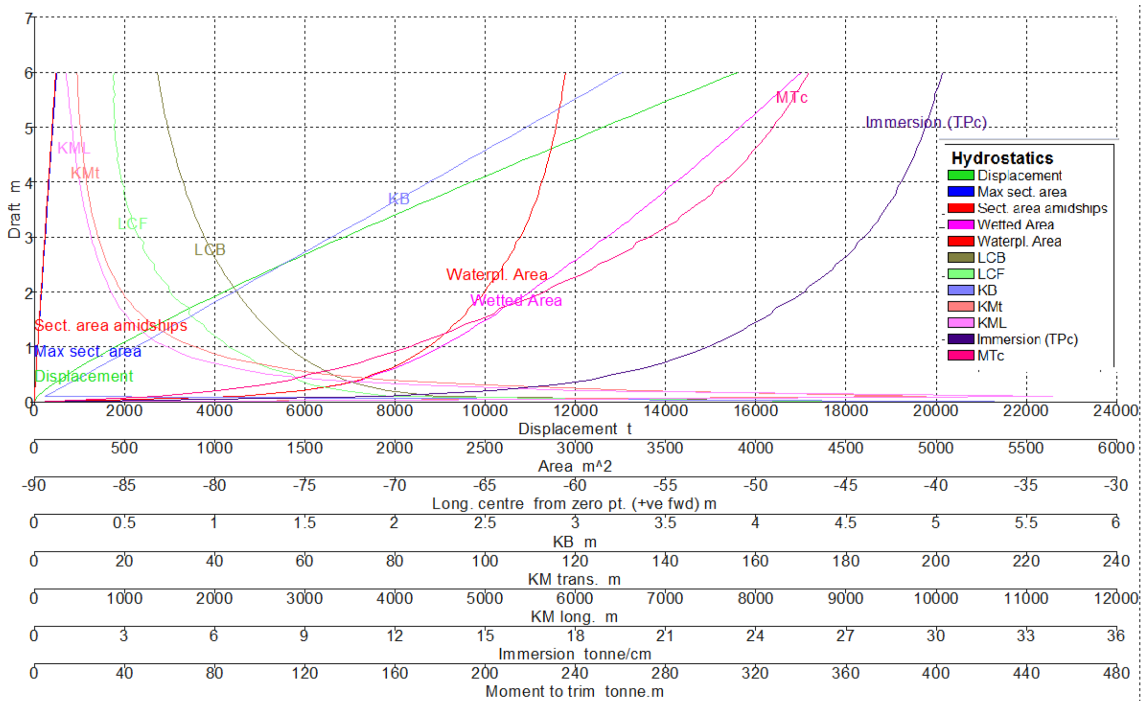

Figure 4.8: ORC hydrostatics particulars

Based on this analysis, the stability of the vessel is shown to be within the regulatory requirements with the overall dimensions established for the concept ORC.

4.4.2 Mooring Analysis

A numerical analysis of the ORC mooring system is conducted using OrcaFlex. The numerical model of the chain mooring layout consists of three groups of two mooring lines, hence a total of 6 catenary mooring lines attached to the turret buoy. The estimated particulars of the vessel and turret buoy in earlier sections are used to provide the vessel model. Each group of catenary lines or anchor legs is 120° apart and each leg consists of studless Grade R4 chain (70 mm diameter) terminating in an anchor pile. A simplified schematic diagram of the ORC mooring arrangement is provided in Figure 4.9. The model is simulated for a water depth of 150 m. A total of four simulations were conducted for a combination of extreme and operational environmental conditions at 0 degree and 180 degree heading of environmental loads. These two headings provided cases where the combined wind-wave-current load acted either on a single mooring line group or was applied between two groups of mooring lines. The vessel was oriented bow to weather for all the simulation cases. The model input parameters are provided in Table 4.8.

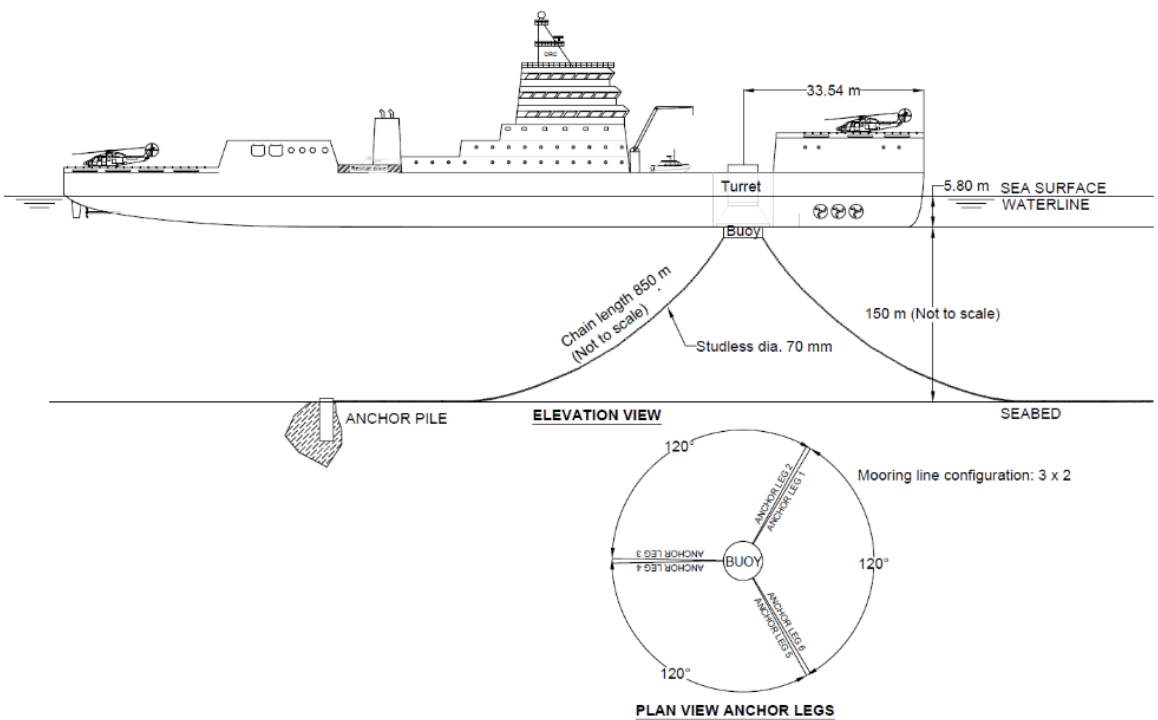

Figure 4.9: ORC mooring leg arrangements

Table 4.8: Model input parameters

Environment		**Parameter**	**Value**	**Unit**
		Seabed depth	150	m
Extreme (Heading: 0 and 180 degree)	Wave	Wave spectrum	JONSWAP	
		H_s	16.00	m
		T_z	20.00	s
		Gamma	2.00	
	Current	Speed	1.38	m/s
	Wind	Speed	33.60	m/s
Operational (Heading: 0 and 180 degree)	Wave	Wave spectrum	JONSWAP	
		H_s	3.23	m
		T_z	8.94	s
		Gamma	1.00	
	Current	Speed	0.22	m/s
	Wind	Speed	9.74	m/s
	Mooring lines (1-6)	**Parameter**	**Value**	**Unit**
	Line properties	Length	850	m
		Radius from buoy joint	815	m
		Cable type	Chain	
		Bar diameter	0.07	m
		Link type	Studless	

The turret and buoy are connected to the ORC through a constraint object that allows the vessel to rotate about the z-axis only. This enables the vessel to weathervane without rotating the mooring lines with it. The effects of wave load (1st order), wave drift load (2nd order), wave drift damping, added mass and damping, current load and wind load are considered in the simulation. Three DOF static analysis is also included that solves the vessel position to equilibrium before dynamic simulation starts. Suitable added mass and damping coefficients are chosen based on previous similar sized vessels. For each case, simulation is run for 1800 seconds and the time series data of leg 3 tensions for the most extreme condition (Case 4: extreme weather and 0 degrees heading) is provided in Figure 4.10. The graph shows several peak tensions at the mooring line crossing 150 ton-force (tef) and the maximum value reaches 320.11 tef in 1290 sec due to a large wave where a major portion of environmental load is transmitted to leg 3. This represents the worst possible scenario as it is seen from Figure 4.11 that maximum tensions are significantly lower than this value for other cases. Also, the maximum tension never exceeds the chain proof load.

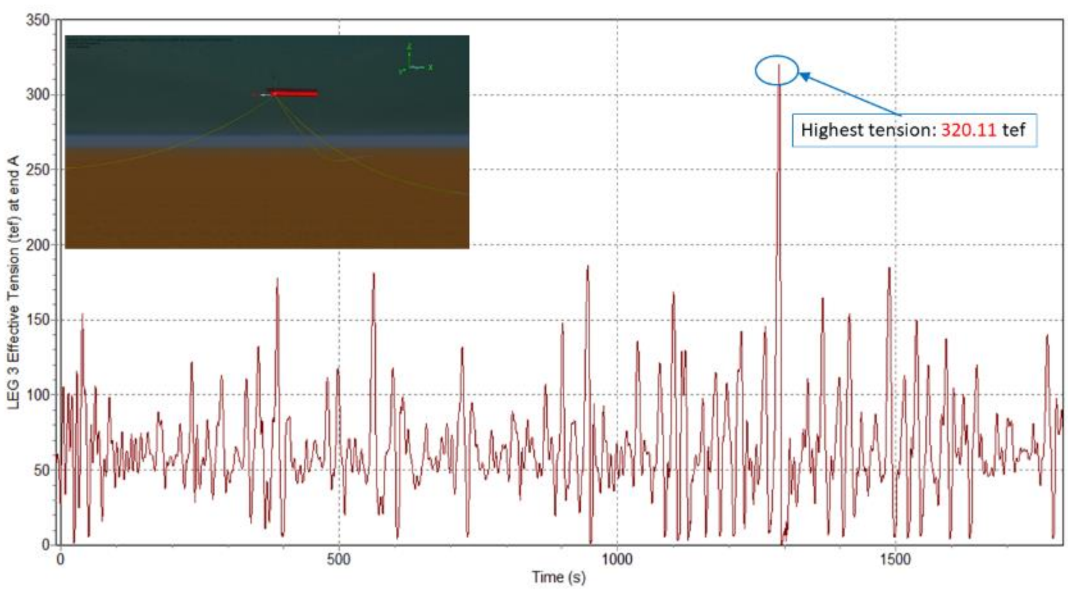

Figure 4.10: Leg 3 tensions for extreme weather and 0 degree weather heading

There is no doubt that the mooring concept can be further refined and considerations such as DP assist for extreme load cases might also be considered in future iterations as a means of reducing the chain size or length. However, this analysis establishes a reasonable first indication of an appropriate mooring concept for the ORC platform.

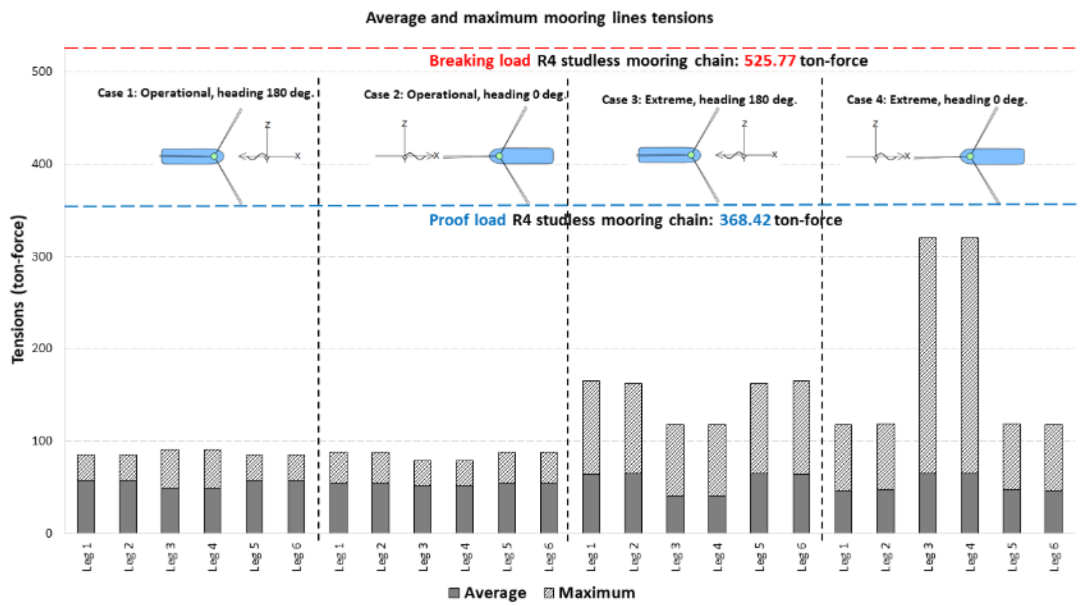

Figure 4.11: Average and maximum mooring line tensions for all 4 cases

4.5 Discussion

In this study a vessel of approximately 160 m length is developed and demonstrated to be a viable conceptual solution to reduce the risk associated with isolated or low density offshore operations, located at extreme distances from shore bases. The main characteristics of the ORC are summarized in Table 4.9. The proposed concept provides an intermediate landing/refueling location for long range helicopter operations and a safe haven in case of changing weather, mechanical or personnel emergency. In the absence of any other landing or staging point between a shore base and a remote offshore platform, a floating vessel type platform specifically developed for the intended purpose may provide the enabling technology for distant offshore developments. In the particular case studied here, a ship-shaped platform is selected due to favorable operating characteristics in ice prone environments.

Since there is no previous basis ship or platform, which has the complete similarity of all the functional requirements of the concept ORC, the functional requirements of the ORC are identified and the space requirements for each functional block are estimated. The blocks are logically arranged to determine the required overall size of the ORC vessel. This method has proven to be a quick and accurate means of concept development for a novel installation and leads to consideration of the required functionality before consideration of vessel size or type. This method for combining capabilities from different marine platforms is shown to be a convenient and workable tool. It offers flexibility in concept development, which can be modified based on the relative importance of various attributes of the ORC and the environmental conditions. The method also allows alternative approaches to be considered for platform development. For example, it may be possible to convert an existing vessel to an ORC as an alternative to a new construction. The process of establishing blocks of functional space requirements would allow alternatives such as conversion to be evaluated in comparison to the purpose built concept presented here.

Table 4.9: ORC Principal Dimensions and Characteristics

Vessel	LOA	159.63 m
	Beam	22.50 m
	Depth	10.10 m
	Draft	5.80 m
Mooring	Type	Disconnectable turret
	Chain diameter	70 mm
	Chain Length	850 m
	Mooring legs	3×2, Catenary chain
Accommodations	Crew	42 persons
	In-transit POB	36 persons
	Temporary stay	Up to 150 persons
Helicopters	Helidecks	2×Large helicopters e.g. Sikorsky S-92
	Hangar	Up to 2 Large helicopters

The two key functionalities considered in this study and concept development are helicopter operations and the disconnectable mooring system. A disconnectable turret mooring system is proposed for station keeping that consists of 3×2 catenary chain mooring lines and a small spider buoy connected to an internal rotating turret. There is some remaining engineering uncertainty around smaller scale turret mooring system, as there are no similar scale vessel systems in existence, but no obvious technical obstacles are found in this analysis. The concept of using a disconnectable turret mooring system for station keeping is a mature technology with similar mooring systems used for the Terra Nova and SeaRose FPSOs, operating in similar environmental conditions. The weathervaning capability improves the ORC operability in the expected sea states and the disconnectable buoy enables the vessel to relocate when required. Proportionally less space is needed on the ORC vessel for the turret installation due to the lack of fluid transfer.

Preliminary design analysis shows that the ship size and dimensions are reasonable and that the conceptually developed mooring size is practical. A static and dynamic analysis of the concept mooring system is conducted using the numerical analysis software, OrcaFlex. Result show that mooring line tensions are within the chain limits although it is recognized that there is likely still considerable room for further refinement. Seasonal ice management may also be used to reduce mooring loads and provide access of supply vessels for cargo handling operations or emergency response.

Helicopter operations are incorporated as two full-sized landing areas at bow and stern of the vessel with a hangar located at the stern helicopter deck. This provides various options for landing, multi-helicopter operations and provision for servicing if required. The vessel size of the ORC provides a more stable landing platform than a smaller supply vessel and the availability of two landing options should provide operational weather limits comparable to the much larger FPSO vessels. Low height helideck arrangements are expected to give better-operating capabilities compared to supply vessels or FPSOs where helidecks are often placed above the height of the wheelhouse. The aft helideck is likely to provide more favorable landing conditions than the forward helideck due to the weathervaning of the vessel, providing a generally into the wind approach. The presence of a hangar can facilitate the storage of helicopter (s) during storm conditions.

Emergency response functionality is also incorporated into the ORC concept as this is also identified as a high risk issue for remote platform operations. The concept is developed as a forward base for response equipment and as a command and control centre for emergency response. Both these functions serve to improve response time which is essentially a risk mitigation strategy more so than the prevention strategy embodied in the idea of an intermediate helicopter base. Thus the platform provides two risk reduction approaches for two of the major risks identified in the previous analysis of long range offshore production operations.

The installation of an ORC with these capabilities in the presented example location provides a single-leg journey distance that is well within the current operating experience and operational limits for existing floating production platforms in the same region. The ORC incorporates accommodations for in-transit personnel and reserves the required resources to support emergencies. This addresses the major challenges for distant offshore operation in harsh environmental conditions and provides a platform to meet the previously identified risk reduction objectives.

This ORC concept, and indeed the overall idea of reducing the logistical support or emergency incident risk factors by the installation of an auxiliary platform located at an intermediate location, represents a conceptually simple idea to enable more remote offshore operations. The ORC concept is shown to fit within a reasonable sized ship envelope, bigger than a supply vessel, but, much smaller than a production platform i.e. FPSO. Capital and operational costs for such a platform would be significant, but the development of a viable platform concept provides the first step in a full evaluation of the costs and benefits of such a risk reduction strategy. Further design iteration would firm up the concept and allow more detailed analysis of the ORC as a risk reduction strategy, including life cycle costs. As a technologically straightforward solution for supporting remote offshore operations in the North Atlantic the ORC concept should be further analyzed and considered.

4.6 Conclusion

As follow-on from a previous risk analysis of permanent offshore production operations in remote and environmentally challenging locations, this study presents the conceptual development of a moored vessel that can be used as an intermediate offshore base for regular logistic support operations and emergency response in a remote harsh environment. The proposed ORC concept study outlines the following unique ideas.

- The concept of this floating vessel may reduce many operational challenges and risks further offshore, particularly in ice-covered regions.
- Since there is no existing vessel/platform that can meet the required missions, a modular/block ship design concept is applied, where the space requirements of each functional block are estimated from similar ship data.
- In the process of concept development, relevant regulations and guidelines for the vessel design are explored that may guide in the future for the physical development of this concept.
- The concept design of the ORC suggests some unique design features such as a disconnectable turret mooring system and helideck configurations. The basis of these design features is also described.

This concept development can be furthered by collecting more practical data and input from the industry but the concept is shown to be technically viable. A cost-benefit analysis should be conducted to study the economic implications of this proposed risk-reduction strategy. This could lead to a framework to optimize the platform concept in both economic and technology terms. The concept here presents a start point for further analysis of what is thought to be one of the very few viable alternatives for the considered operational scenario.

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5. Risk-Based Cost Benefit Analysis of Offshore Resource Centre to Support Remote Offshore Operations in Harsh Environment

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A version of this manuscript has been submitted to the Journal of Reliability Engineering and System Safety. Minor revisions are received on this manuscript and a revised version of this manuscript is submitted to this journal. Along with the co-authors, Bruce Colbourne and Faisal Khan, the lead author Md Samsur Rahman formulated the problem and developed the model. Md Samsur Rahman performed literature review, developed the methodology, performed analysis, investigation, prepared original draft and revised the draft based on the co-authors' feedback. Bruce Colbourne supervised and contributed in developing the methodology, data analysis, writing - review & editing. Faisal Khan supervised and helped in developing the methodology, writing - review & editing, project administration, funding acquisition.

Reference: *Rahman, M.S., Colbourne, B., Khan, F., 2020. Risk-Based Cost Benefit Analysis of Offshore Resource Centre to Support Remote Offshore Operations in Harsh Environment, currently submitted to Reliability Engineering & System Safety for review.*

Abstract

Marine Logistics support during regular and emergency operations in remote North Atlantic regions is risky due to longer helicopter flying distances and extreme environmental conditions. In this paper, the safety and economic aspects of a previously introduced concept of an intermediate offshore resource centre (ORC) are evaluated (Rahman et al, 2020a, b). The ORC goals are to provide an intermediate helicopter landing station and a forward staging area for emergency response. Among many advantages, ORC mitigates the logistical risk associated with the extended distance from shore support by reducing the response time in the case of accidents. This paper focuses on presenting a risk-based cost-benefit analysis of the ORC. A probabilistic loss function model is developed based on the costs of historical offshore blowout incidents and their corresponding response times. The cost and benefit model is simulated in a probabilistic framework using a Monte Carlo simulation. The developed methodology and model help to assess the financial viability of an ORC assist in informed decision-making regarding risk reduction measures.

Keywords: Risk Analysis; Offshore Logistic Support; Loss Modelling; Offshore Support Centre; Risk-based decision; Offshore Safety.

5.1 Methodology to Develop Logistics Risk Model

Activities in remote northern offshore regions are expected to increase, due mainly to available hydrocarbon resources. The extended distance from shore support and the inherent harsh environment comprising generally high winds and waves, fog, freezing temperature, and the presence of seasonal ice all pose significant logistical challenge in maintaining regular operations (Hamilton, 2011; Khan et al., 2014; Meling, 2013; Necci et al., 2019). Also, a quick response cannot be provided in case of emergency due to the long distance between shore and the platform(s). The risk associated with the logistical support operations is analyzed in two previous studies (Rahman et al., 2020a,b; 2019) and a risk mitigating Offshore Resource Centre (ORC) concept is presented in (Figure 5.1) Rahman et al., 2020b. The ORC has two primary mission requirements for cases where an offshore development is exceptionally remote from land-based support:

- Provide an intermediate point for helicopter operations that enables refueling, alternate landing and shorter transit distance.
- Provide a forward staging or response asset for emergency response in case of fire, spill, sinking or ice damage.

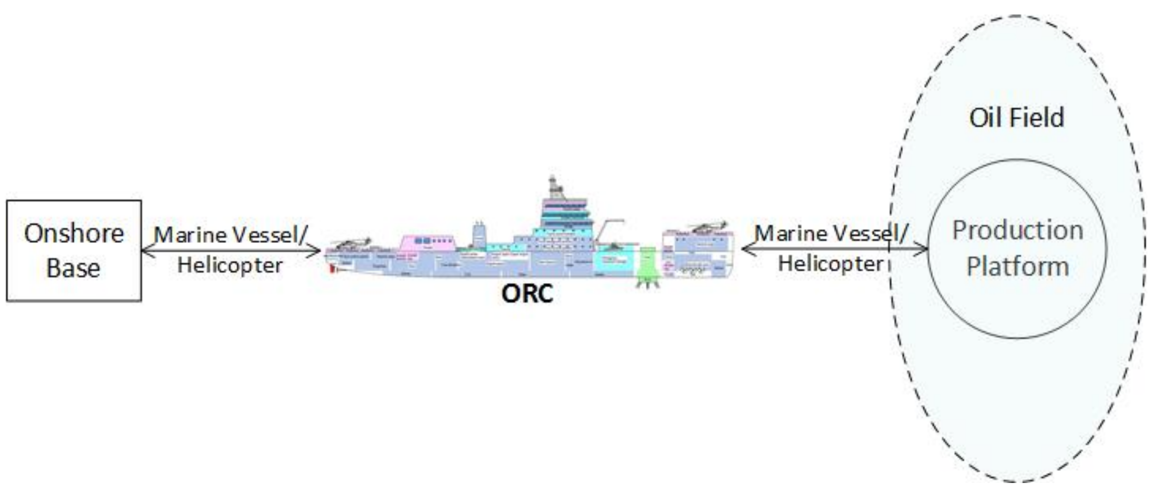

Figure 5.1: A solution for logistics support and emergency response in remote harsh environments [revised after Rahman et al., 2020b]

As a risk reduction strategy, the cost of an ORC would be a significant fraction of the development cost for a remote offshore development. Thus it would be beneficial to have a rational methodology for comparing the costs and benefits of the ORC. These costs and benefits are evaluated in this paper based on the benefit scenario of response time reduction for a blowout accident. This evaluation considers only one of the two main functions of the proposed ORC but provides a methodology which would allow all functions of the intermediate platform to be evaluated by comparing costs to potential savings in an operational or emergency scenario.

The first step is to estimate the capital cost of the ORC. There are various methods available for cost estimation in the shipping business. Caprace and Rigo (2012) classified the methods for estimating production cost into three categories, namely, top-down, bottom-up, and life cycle approaches. In a top-down approach, the cost of a new ship is estimated from the parametric relationships of similar historical ship cost data using statistical regression analysis. This approach does not require the detailed specifications of the new ship. It provides a high-level cost estimate under the assumptions that vessels have similar functionalities and construction procedures remain the same. In a bottom-up approach, the project is broken down into smaller and smaller intermediate products until the most basic product is described. This approach is suitable when the detailed design particulars of a new building ship are available. In this study we have used the top-down method and adapted data from other ship types as there is no historical data for the new concept ORC.

The second stage is to estimate the life cycle cost (LCC) of the ORC, which is the present value of total cost that it may encounter over its life cycle. This includes building cost, operational cost, maintenance cost and scrap. The LCC approach is a promising holistic approach to estimate the cost of the overall life of a ship. Since the ORC is in the concept design phase, the cost estimation is possible only at a very high level and this requires rather broad assumptions about the ship design, its general functional requirements, and its physical and operational characteristics (Lamb, 2004).

The capital and life cycle costs make up the cost side of the equation. The benefits arise from the functions of the ORC system. One of two primary functions of the ORC is to mitigate risk by reducing response time when a remote offshore platform is in danger. In general, this should minimize the loss of production or the platform. This risk reduction, particularly in the consequences of an accident can be considered as a financial benefit. Inherent in this logic is the assumption that a faster response in the case of an accident results in reduced loss. This is particularly true when environmental damage from a blowout is considered.

The use of a loss function (LF) is a structured approach to estimate the loss arising from an incident. Loss functions (LFs) express losses related to the deviation of a product from its optimal value. In recent years loss functions have gained wide acceptance among researchers and quality assurance practitioners due to Taguchi's philosophy and quality improvement strategies (Zadakbar et al., 2015; Spiring, 1993). Several types of loss functions are found in the literature such as quadratic (Taguchi, 1986), inverted normal (Spiring, 1993; Khan, et al. 2016), inverted beta (Leung & Spiring, 2002), inverted gamma loss function (Spiring & Yeung, 1998; Leung & Spiring, 2004), etc. The loss of a production platform leads to production downtime, loss of material assets, loss of human lives and environmental damage. This loss is linked with the risk of an accident in a production platform.

A main contributor to the total risk is the uncontrolled release of pressurized hydrocarbons, i.e., gas leakages and blowouts. In this paper, costs data from previous blowout incidents are used to develop a loss function. The details of the historical data are described in the case study section. Adopting a deterministic approach would be unsuitable due to the scarcity of data and the variability in previous accident circumstances. Hence, the complete analysis is conducted in a probabilistic framework using the Monte Carlo Simulation (MCS) technique. The methodology proposed in this paper aims to:

- estimate the building cost and operational cost of the ORC from historical ships data and recent offshore operational day rates and establish a net present value (Cost model);

- develop a loss function model from past offshore platform blowout accidents and project this data to present day figures (Benefit model);
- integrate the cost and benefit model in a probabilistic framework, and
- determine a break-even probability for an offshore development considering ORC as part of risk reduction strategy.

The paper is organized as, Section 5.1 provide general basis of ship cost estimation and a review of relevant literature on LFs. The methodology of this study is presented in Section 5.2. A case study to demonstrate the methodology is presented in Section 5.3. Discussions and conclusions are presented in Sections 5.4 and 5.5, respectively.

5.2 The Proposed Methodology

The methodology proposed here comprises three elements: cost model, benefit model and integrated probabilistic cost - benefit comparison. The flow chart of the proposed methodology is given in Figure 5.2.

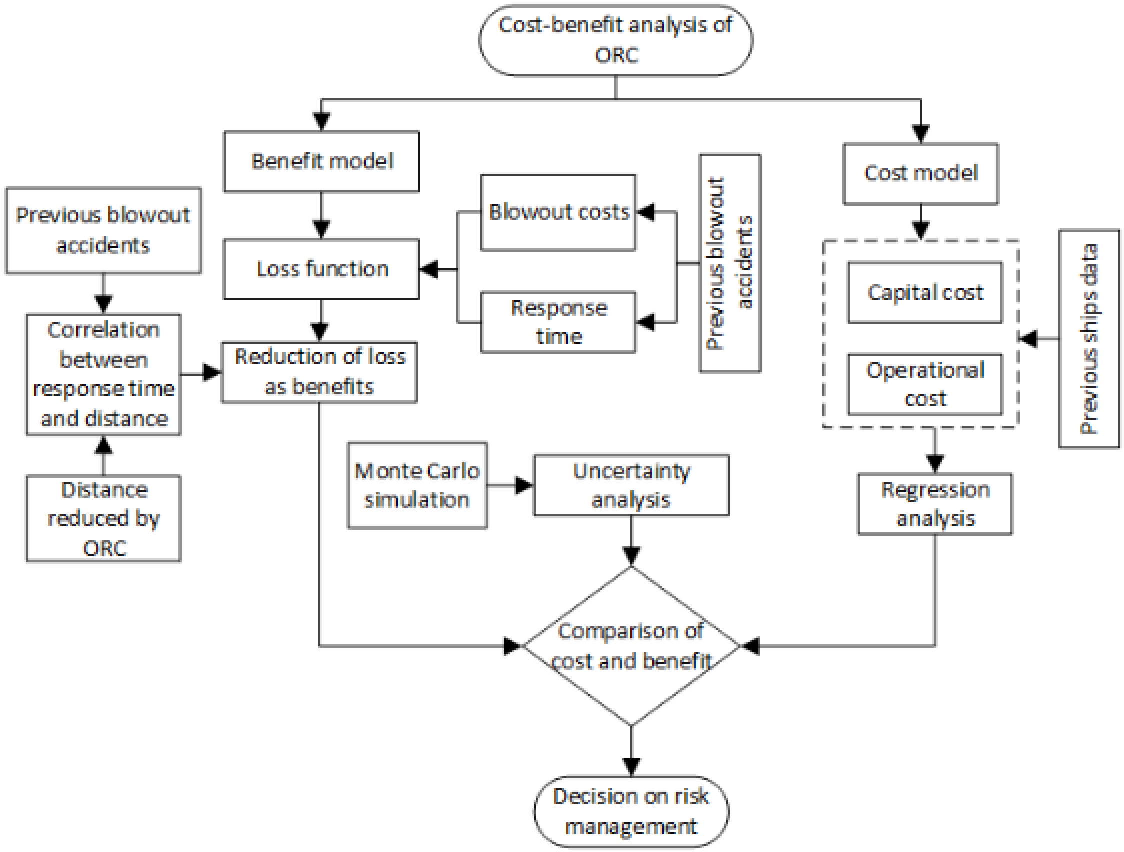

Figure 5.2: Flow chart of the proposed methodology

5.2.1 Cost model

The total cost of the ORC includes capital cost and operational cost. Recent historical ship cost data are used to develop a capital cost model based on principal particulars, in a multiple linear regression. Then, the principal particulars, i.e. ship length, beam, year built, of the ORC, are used in the regression to develop an estimated capital cost for the ORC. Multiple linear regression (MLR) is a simple statistical technique that uses several independent variables to predict the outcome of a dependent variable. Multiple regressions are based on the assumption that there is a linear relationship between both the dependent and independent variables. It also assumes no major correlation between the independent variables (https://www.investopedia.com/terms/m/mlr.asp). A general expression for a MLR model with k independent variables X_1, X_2, ..., X_k and a response or dependent variable Y, can be written as (equation 5.1):

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \epsilon \tag{5.1}$$

where ϵ is the residual term (error) of the, model and β_0, β_1, β_2, ..., β_k are the regression coefficients in the model.

The operational cost of the ORC is the working cost over its design life. Since the ORC has unique functionalities, it is difficult to find an exact match with previous vessels. It is judged that platform supply or standby vessels are the closest comparison with the ORC. Considering the size of these vessels, the daily charter rate of two offshore supply vessels are assumed in the present case to be approximately equal to a ORC daily operational cost. In this way, the total operation cost of the ORC is calculated over its design life of 25 years using 2x the current day rate of a typical northern offshore supply vessel as a proxy for all costs including crew, maintenance, fuel, provisioning and financing. The net present value (NPV) is used to estimate the current value of future payouts over the life of the system. NPV is the difference between the present value of cash inflows and the present value of cash outflows over a period of time (https://www.investopedia.com/). In this case we only consider cash outflows and NPV is calculated as (equation 5.2):

$$NPV = \sum_{t=1}^{n} \frac{R_t}{(1+i)^t} \qquad (5.2)$$

where R_t is the net cash inflow-outflows during a single period t, i is the discount rate or return that could be earned in alternative investments and t is the number of time periods.

The capital cost and operational cost estimated from the process described above are summed to get the total cost of ORC.

5.2.2 Benefit model

In this study, the benefit is defined as the financial value of the reduction of loss when an ORC is installed as a risk mitigation measure. Emergency response would take longer to a remote offshore platform than it would for platforms that are closer to shore support. This limitation of response time was identified as a key risk factor in the previous analysis of remote offshore installations (Raman et al., 2019). In essence, the ORC decreases response time as it will be closer to a hydrocarbon facility than any shore base for support. Previous offshore accident data related to significant response time and the distance are used to develop an empirical relationship between these factors.

The next step is to develop a loss model with respect to response time for offshore blowout incidents. Previous blowout incidents are used to develop this model. The ultimate cost of a blowout incident is difficult to estimate. The cost accrues from damage or total loss of platform, loss of human lives, production downtime or shut down, oil cleanup cost and other environmental cost, liabilities and lawsuits, etc. Figure 5.3 shows the breakdown of total costs or maximum loss (Marsh Risk, 2011). There are some hidden costs arising from the revenue lost, profit not earned or reputation damaged due to an accident that may not be recognized under a purely financial reporting system (Lee et al., 2018). For instance, BP reported the total costs of the Deepwater Horizon oil spill as 62.59 billion USD, which includes charges and expenses directly related to the spill, the various fines and penalties to be paid, reimbursements and recoveries from other parties, and securities-related charges. However Lee et al., 2018 estimated the ultimate cost of this disaster as 144.89 billion USD including the hidden costs.

The additional cost is largely influenced by the environmental cleanup cost that depends on the occurrence of a spill and the location of the accident. In general, cleanup cost increases when a spill occurs and rises exponentially when an oil spill occurs near to shore. In addition the damage to company reputation, share value etc. is also likely increased by the increased publicity associated with spills that damage shorelines. Examples of this type of loss include the Deepwater Horizon and the Exxon Valdez spill. To address the hidden cost issue, an environmental cleanup factor is introduced to capture the non-financial costs, particularly for spills that damage shore line areas. This factor for spills that damage shorelines is essentially the ratio between costs as estimated by BP for the Deepwater Horizon incident and the higher cost calculated by Lee et al., 2018 A lower but arbitrary cleanup factor is used for cases where a spill occurs but does not impinge on a shoreline. All historical cost data collected from the literature are converted to present value for the year 2020 by considering inflation rates.

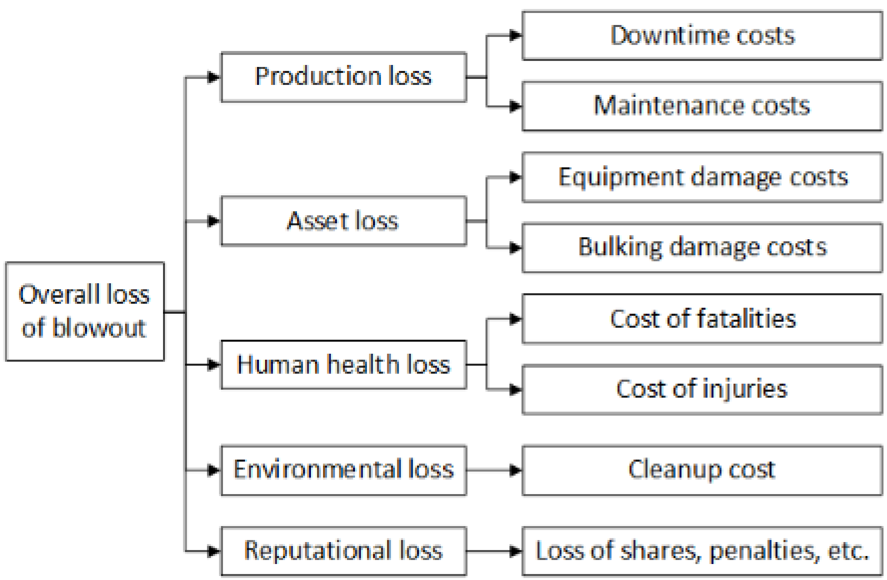

Figure 5.3: Breakdown of overall blowout loss

Statistical parameters are derived from the inflated accident cost data set and are used to generate a Cumulative Density Function (CDF) for financial losses associated with an offshore blowout. An appropriate probability distribution is selected that best fits the data. Parameters are estimated using the least square method. The same process is applied to generate a CDF for emergency response time based on the statistical parameters derived from the response times from the historical incidents. A loss curve is generated by comparing the CDFs of costs and response time and equating the cost values and response time values based on equal values of cumulative probability. This provides a curve of accident cost as a function of response time based on equal cumulative probability of occurrence.

The final step in the setup process is to derive a curve of response time as a function of offshore distance. This is based on the available data and, like all the data in this study, is limited by the relatively small sample of offshore blowout accidents. Furthermore our study considers a very remote platform and thus the distance for the unsupported platform is well outside the range of previous accidents. In extrapolating the limited information available we have assumed that the response time would increase exponentially as distance offshore increases.

5.2.3 Aggregate cost and benefit model

The cost and benefit models described in section 5.2.1 and section 5.2.2 are integrated to calculate the net, which is referred as "residual risk" (R_r). The steps are as follows:

(1) Estimate the capital and operating costs for the ORC with operating costs for 25 years reduced to a net present value

(2) For a given accident scenario, the required response time is derived from response time vs offshore distance curve for the platform without the presence of an ORC.

(3) Calculate the cost of the accident from the loss model for the corresponding response time.

(4) Use the reduced distance between the ORC and offshore platform to calculate a reduced response time

(5) Repeat step 3 to calculate the reduced costs of accident using the response time with the support of the ORC.

(6) Determine the difference in loss costs for the with-ORC and without-ORC cases.

(7) Compare the difference in loss costs with the expense of acquiring and operating an ORC. Develop a break-even accident probability based on a cost vs accident probability curve.

Hence, R_r is determined as (equation 5.3):

$$R_r = P_a(L - L_{ORC}) - (C_p + C_o) \tag{5.3}$$

Where P_a represents the probability of accident, L is the cost of the accident calculated from the loss function, L_{ORC} is the cost of the accident when the ORC is installed. C_p and C_o represent the capital cost and operational cost of the ORC, respectively. Risk is defined as the multiplication of probability and consequence. The consequence of an accident is often expressed as loss.

In this study, the probability of blowout incidents is unknown but the design level for offshore systems is frequently in the range of 10^{-5}. Despite this, blowout accidents have happened at approximately 10 year intervals since the 1960s. Using equation 5.3, we can determine that an ORC is a positive investment if the value of R_r is positive. Thus another way to consider the analysis is to determine what accident probability makes R_r greater than zero.

5.2.4 Uncertainty analysis

It is recognized that the historical cost and historical accident data used in this study are not entirely sufficient but these are the only data available as cost data is not widely available and offshore accidents, although well studied in recent years, have been mercifully few. The data paucity requires that, for the purposes of this analysis, several assumptions are made. The Monte Carlo simulation technique is adopted as an additional way to address this limitation. In this approach, a probability distribution of each cost part is used instead of a deterministic value. It is assumed that all calculated costs and benefits are normally distributed with mean (most likely) values calculated from the available data and standard deviations either based on regression data (in the case of ship costs) or assumed equal to 20% of the corresponding mean value. The Monte Carlo simulations are run for n times and a histogram is ultimately generated for R_r using equation 5.3. The characteristics i.e. mean, 50th percentile, etc. of this distribution are further investigated to inform the decision on the viability of an ORC.

5.3 The Application of the Proposed Methodology: Case Study

5.3.1 Example location of ORC

The Flemish Pass Basin is chosen for a case study to illustrate the cost-benefit analysis of an ORC and a hypothetical hydrocarbon platform that may operate in this region. The

Flemish Pass basin is located approximately 500 nautical miles offshore St. John’s, Newfoundland and Labrador. Equinor Canada Ltd. (Equinor) is proposing to conduct an exploration drilling project in the Flemish Pass Basin between 2019 and 2027 (Canada Impact Assessment Act, 2019) although this is currently uncertain due to low oil prices.

As conceptualized in the previous study, the proposed ORC would be located at an intermediate location between the shore (St. John’s) base and the drilling sites (Rahman et al., 2020a,b). The ORC concept includes defining functional requirements, initial dimensions estimation and addressing some critical design features required to operate at the selected site. Table 5.1 provides the basic characteristics of the proposed ORC. The following sections describe the cost estimation for this ORC, loss approximation for a hypothetical offshore blowout incident and analysis of loss cost reduction through the use of the ORC as a risk reduction measure.

Table 5.1: ORC Principal Dimensions and Characteristics

Vessel	LOA	159.63 m
	Beam	22.50 m
	Depth	10.10 m
	Draft	5.80 m
Mooring	Type	Disconnectable turret
	Chain diameter	70 mm
	Chain Length	850 m
	Mooring legs	3×2, Catenary chain
Accommodations	Crew	42 persons
	In-transit POB	36 persons
	Temporary stay	Up to 150 persons
Helicopters	Helidecks	2×Large helicopters e.g. Sikorsky S-92
	Hangar	Up to 2 Large helicopters

5.3.2 Cost estimation of the ORC

As mentioned earlier, the ORC is a unique vessel type that does not match with any existing type of ship. At the concept stage, it is not possible to estimate cost by detail calculation of every part of the vessel system. Thus, to make a reasonable initial estimate, building cost data from recent cruise ships are used. Cruise ships fall into a middle category in terms of ship construction complexity as these vessels are less expensive than military ships but generally more expensive than similar sized commercial cargo or working ships. The construction cost of an ORC may also fall into the middle range of construction complexity considering the machinery requirements i.e. turret mooring, accommodation and recreational facilities and provision for aviation facilities. This shows some justification for comparing the costs of cruise ships and the expected cost of an ORC. Furthermore construction cost data for cruise vessels is readily available and appears to be less variable than the data available for other ship types. The construction costs of different cruise ships having overall length between 157m – 200m and beam between 22m – 25.6m are shown in Figure 5.4 (https://www.cruisemapper.com/wiki/759-how-much-does-a-cruise-ship-cost).

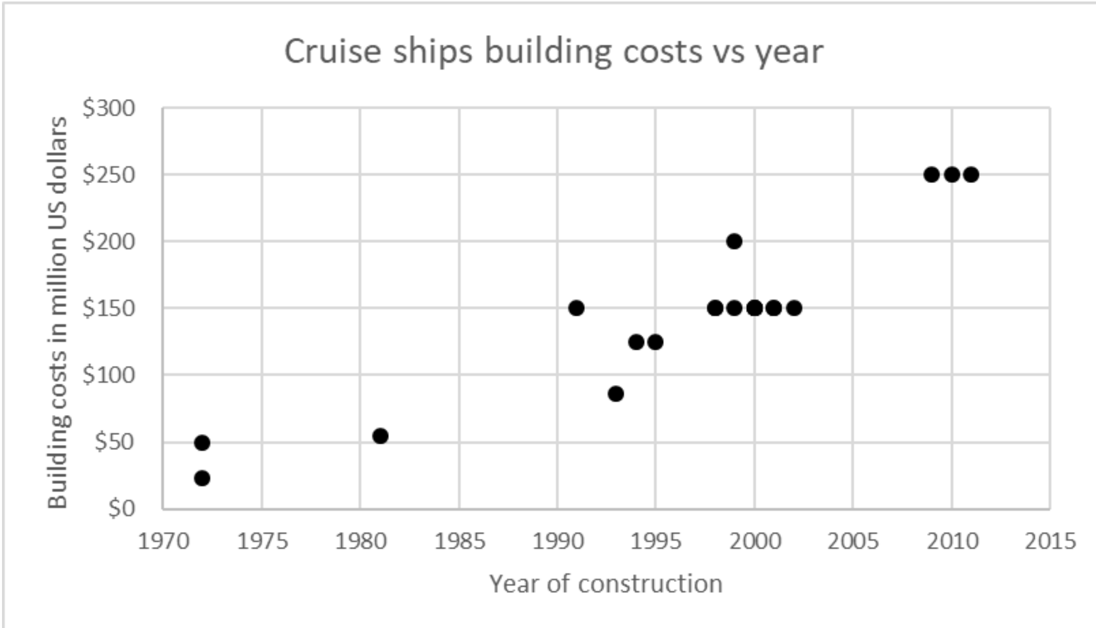

Figure 5.4: Cruise ships building costs vs year

A multiple linear regression is conducted where year, ship's length and beam are independent variables and ship construction cost is the dependent variable. Using the corresponding length, beam and current year, the construction costs of the ORC is calculated as 252 million USD. Table 5.2 provides the summary of this regression analysis and regression equation is provided in equation 5.4.

Table 5.2: Regression analysis of ORC cost

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3.00	62735.68	20911.89	35.87	1.43E-07
Residual	17.00	9912.13	583.07		
Total	20.00	72647.81			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	-10466.58	1128.71	-9.27	0.00	-12847.95	-8085.21
Year Built	5.24	0.58	9.09	0.00	4.02	6.46
Ship Length OA (m)	0.46	0.51	0.90	0.38	-0.62	1.54
Ship Beam (m)	2.66	5.40	0.49	0.63	-8.74	14.06

$$ORC\ Building\ Cost\ (Million\ US\ dollars) = 5.24\ \times Year\ Built + 0.46\ \times Ship\ Length\ OA\ (m) + 2.66\ \times Ship\ Beam\ (m) \tag{5.4}$$

Operational cost of the ORC is calculated from the day rates of US Gulf supply vessels based on data available for 2017 (https://www.workboat.com/resources/reports/osv-day-rates/). The cost is considered to be doubled by comparing the physical and expected crew sizes of the ORC with typical north Atlantic supply boats. Next, the cost is converted to net present value for an operation life of 25 years and a discount rate of 5%. At the present time no allowance is made for inflation or cost changes over the life of the development. Thus, the total lifetime cost of the ORC is given in Table 5.3.

Table 5.3: Total costs of ORC

Daily rate of a supply ship	$25,000	USD
Estimated ORC daily rate (2 times of a supply ship compared to their size)	$50,000	USD
Annual ORC cost	$18,250,000	USD
NPV Operating cost (5% discount rate for 25 years)	$257,214,488.33	USD
Operation cost	$257.21	Million USD
Building cost	$252.11	Million USD
Total life cycle cost of ORC	$509.32	Million USD

5.3.3 Offshore blowouts and corresponding loss function

Offshore oil production is a complex operation. To ensure safe operations all equipment has to be functional and correct decisions have to be made. There is a significant risk associated with undesirable events that may lead to minor or major production loss. Minor events such as near-miss, dropped objects, or production interruptions are more frequent than major accidents involving significant spills or major damage or platform loss. This study focuses on the case of a catastrophic offshore accident (blowout) that represents maximum consequence or loss. There is a relatively small number of historical offshore blowouts. The most costly and latest blowout event is the Macondo well explosion that occurred on April 20, 2010. The platform was located approximately 50 miles off the coast of Louisiana in the Gulf of Mexico. This accident caused 11 fatalities, the sinking of the Deepwater Horizon, and massive marine and coastal damage from a reported 4 million barrels of released hydrocarbons (CSB report, 2016). The Deepwater Horizon oil spill is regarded as one of the largest environmental disasters in North America. Lee et al., 2018 estimated an ultimate cost to British Petroleum (BP) of $144.89 billion, which is more than two times larger than the $62.59 billion BP reported in its income statement.

The Montara wellhead blowout is another recent disaster that happened on August 21, 2009, and which is considered one of the largest in Australian history. The Montara field is located 160 miles off the Kimberley coast in the Timor Sea. There were no fatalities or injuries, however, according to the Australian Maritime Safety Authority (AMSA), the oil slick spread over 6,000km^2 and killed significant marine life in the area. Unlike the Macondo incident, the Montara accident did not have effects on any coastline although the Indonesian government has claimed damages (https://www.offshore-technology.com/features/montara-oil-spill-timeline/).

The Piper Alpha explosion disaster on July 6, 1988, killed 167 people making it the incident with the highest fatality level. This platform was operating in the North Sea approximately 120 miles north-east of Aberdeen, Scotland (Oil & Gas UK, 2008). The total loss from the Piper Alpha explosion was estimated to be $1.6 billion. Initial emergency response arrived after a few hours of the accident, due significantly to the proximity of other production platforms. The platform was completely lost, but no oil spill occurred as the production was mainly gas.

The Ekofisk Bravo explosion in April 1977, was the largest blowout in the North Sea. The platform was located about 200 miles offshore southwest of Stavanger. All crew members on board were safely evacuated. The blowout caused a continuous discharge of crude oil through an open pipe 20 meters above the sea surface that took 7 days to stop completely. Approximately 80,000–126,000 barrels of oil spilled during this period (https://incidentnews.noaa.gov/incident/6237).

The Santa Barbara oil spill occurred on January 28, 1969, due to a blowout 6 miles offshore of Santa Barbara, California. The blowout resulted in about 100,000 barrels of oil spilled that quickly hit the near shore (https://incidentnews.noaa.gov/incident/6206). Cost and other data for this incident are not widely available.

The summary data pertinent to this study for each blowout incident are provided in Table 5.4. In general there is much more information available for the two recent incidents than there is available for the three older incidents. The literature study suggests that oil cleanup cost was typically much higher when the spill happened near to the shore. Thus, higher arbitrary environmental cost factors are chosen for BP Mocando and Santa Barbara blowouts. The total costs of these accidents in the year 2020 are projected considering inflation and environmental cost factor.

Table 5.4: Previous offshore blowouts

	Year	Total Cost (Billion US Dollar)	Significant Response Time (Days)	Total Time	Miles Offshore	US Inflation to 2020	Inflated US Dollar cost	Arbitrary Environ Cost Factor	2020 Total Cost
BP Macondo	2010	62.6	3	87	41	1.192	74.6	2.3	171.6
Australia Montara	2009	1	9	75	160	1.188	1.2	1.2	1.4
Piper Alpha	1988	1.6	1	10	120	2.252	3.6	1	3.6
Ekofisk Bravo	1977	0.75	2	7	200	4.498	3.4	1.2	4.0
Santa Barbara	1969	0.2	1	90	6	7.361	1.5	2.3	3.4

The significant response time in days is the time taken to mount an effective emergency response at the accident site. This would not count initial efforts to rescue or aid survivors from nearby vessels or first-on-site aircraft, but would be the start of efforts to salvage the platform or deal with the blowout itself. Logically, a significant emergency response takes longer to reach an incident as the distance of the platform from the shore support base increases. A response time vs offshore distance curve is plotted in Figure 5.4 based on the data presented in Table 5.4. The graph shows a similar correlation to that stated above but there is clearly a great deal of variability. Part of this variability can be associated with the availability of resources and infrastructure from other similar operations in the region of the incident. This factor would tend to reduce response times in regions such as the North Sea or the Gulf of Mexico and increase response times in more remote or less developed regions.

It is recognized that the data is limited. Also, there are several other factors that may affect the speed of response. More detail of other limitations is presented in the preceding study, Rahman et al., 2019. An exponential curve is fitted in Figure 5.5 relating response time and distance. This fit curve indicates that it would take slightly over 12 days to respond for the example location, which is about 500 miles offshore. Placing an ORC in an intermediate position would reduce the response time considerably, to approximately four days. In the present case we assume the ORC is located at the mid-point between shore and the offshore platform location within 250 miles of the production platform, but the location of the ORC can be optimized to improve response time advantages for any specific site.

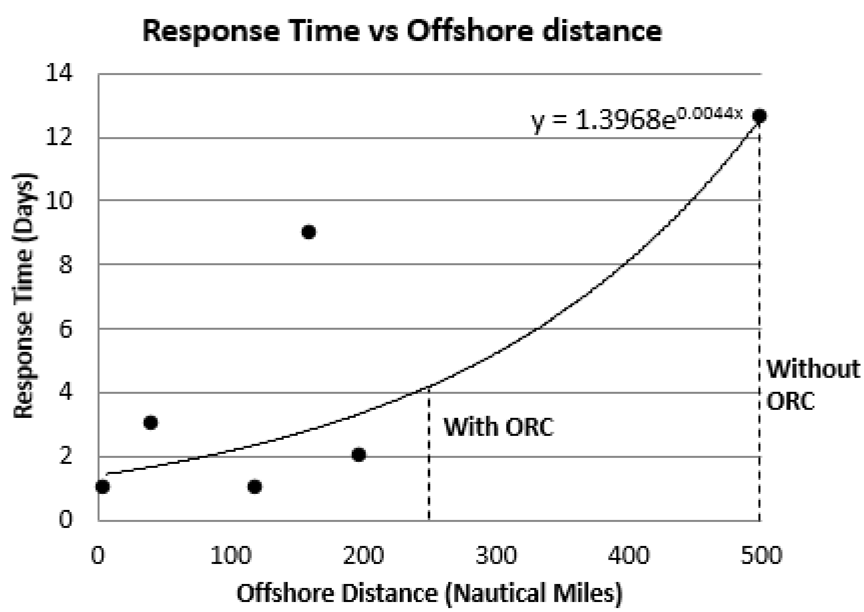

Figure 5.5: Response time vs offshore distance curve

Next, the mean and standard deviation of the blowout costs and response time data are used to generate two corresponding cumulative density functions (CDFs). The data are tested for goodness of fit using various probability distribution and similar curves are found. In this study, the normal distribution was found to provide a good fit and is used to model blowout cost (Figure 5.6) and response time (Figure 5.7).

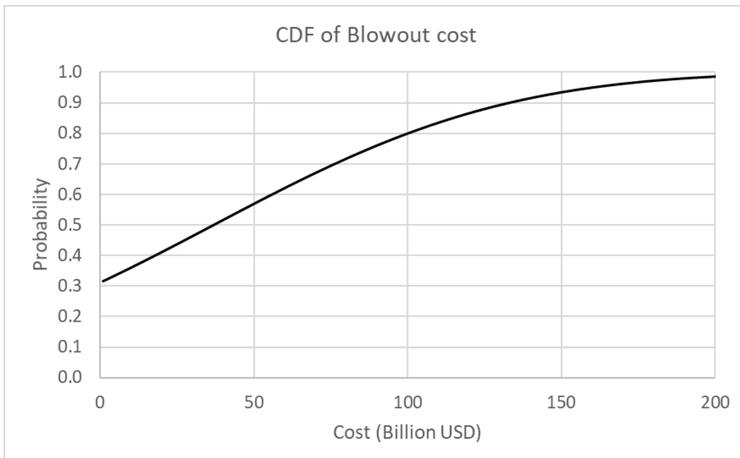

Figure 5.6: CDF of blowout cost

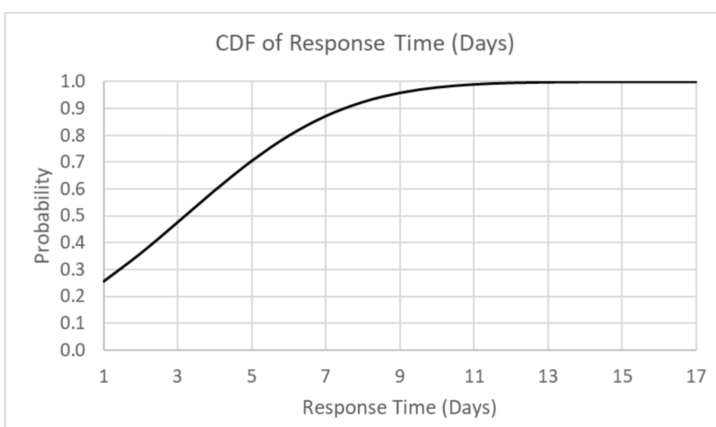

Figure 5.7: CDF of response time in days

A loss curve (Figure 5.8) is generated by comparing the CDFs of the loss costs and the response time and equating the loss values and response time values, based on equal levels of cumulative probability. This provides a curve of accident loss cost as a function of response time based on equal probability of occurrence. The loss function shows that loss increases at a lower rate if the response can be marshalled within 2 days. After that the loss increases sharply as the response time increases and reaches a maximum at 11 days. This statistical model is consistent with the information in the available historical literature on offshore incidents as delayed response generally resulted in a higher cleanup and environmental costs.

Figure 5.8: Offshore blowout loss curve as a function of response time

5.3.4 Comparison of Cost-benefits and Monte Carlo simulations

The estimated cost of the ORC in section 5.3.2 and the difference in loss costs for the with-ORC and without-ORC cases using the models developed in section 5.3.3 are integrated in this section to provide the cost-benefit model. The residual risk is calculated using equation 5.3. The probability of an accident, P_a is needed to get the complete risk profile. A positive residual risk means the value of the reduced risk due to the presence of the ORC is greater than the cost of providing the ORC, for a given value of the probability of a blowout incident. The residual risk is higher when the probability of an accident is increased.

Due to the inherent uncertainty in the available accident data, the Monte Carlo simulation technique is used to determine a distribution of outcomes. A probability distribution of each element in equation 5.3 is used instead of a deterministic value. It is assumed that costs are normally distributed with mean (most likely) values calculated from the loss functions and standard deviations either based on regression data (in the case of ship capital cost) or assumed equal to 20% of the corresponding mean value. The simulations are run 1000 times for a given probability of accident. A sample simulation is provided in Table 5.5. Figure 5.9 shows a histogram for residual risk (R_r) when it is assumed that a blowout has occurred i.e. the probability is 1. The mean, standard deviation, 5th percentile and 95th percentile are also given. These values represent the probable highest residual risk or the maximum net value that can be gained through the installation of an ORC for the given scenario.

Table 5.5: Monte Carlo simulation of cost-benefit analysis

Scenario	Offshore distance (Miles)	Response time (Days)	Loss cost in Billion USD	Probability of accident P_a
Without ORC	500	12.61	200.00	1.0000
With ORC	250	4.20	58.98	
Statistical parameters	Loss without ORC (Billion USD) L	Loss with ORC (Billion USD) L_{ORC}	Capital cost of ORC (Billion USD) C_p	Operational cost of ORC (Billion USD) C_o
Expected	200.00	58.98	0.25	0.26
Standard Deviation	40.00	11.80	0.02	0.05
First simulation	183.00	75.62	0.23	0.29
Residual risk	106.86			

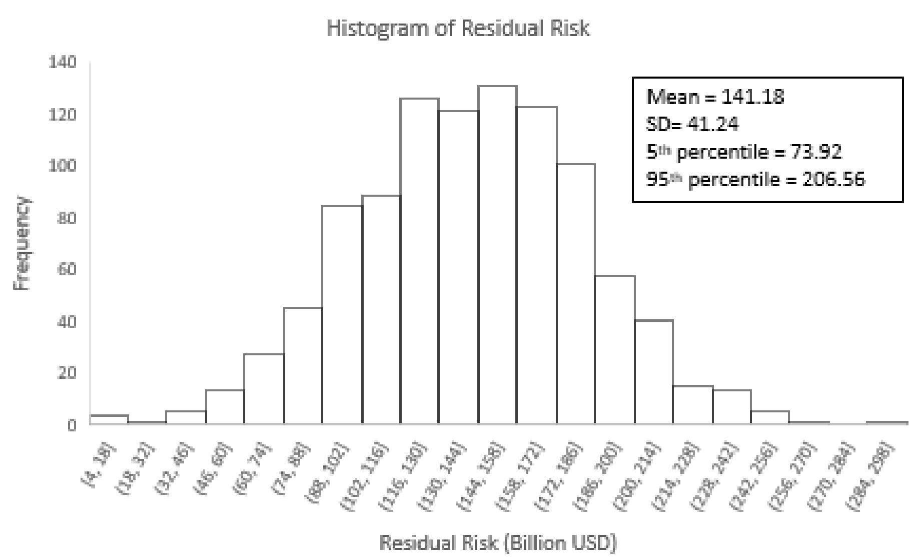

Figure 5.9: Histogram of residual risk

Figure 5.10 shows the mean and standard deviation of residual risk for different probabilities of blowout accident. It shows that the mean and standard deviation of the residual risk decreases as the probability of accident decreases. The risk becomes zero when the probability is approximately 0.00365, which is the breakeven point. Hence, ORC is a net benefit when the probability of accident is higher than the breakeven point.

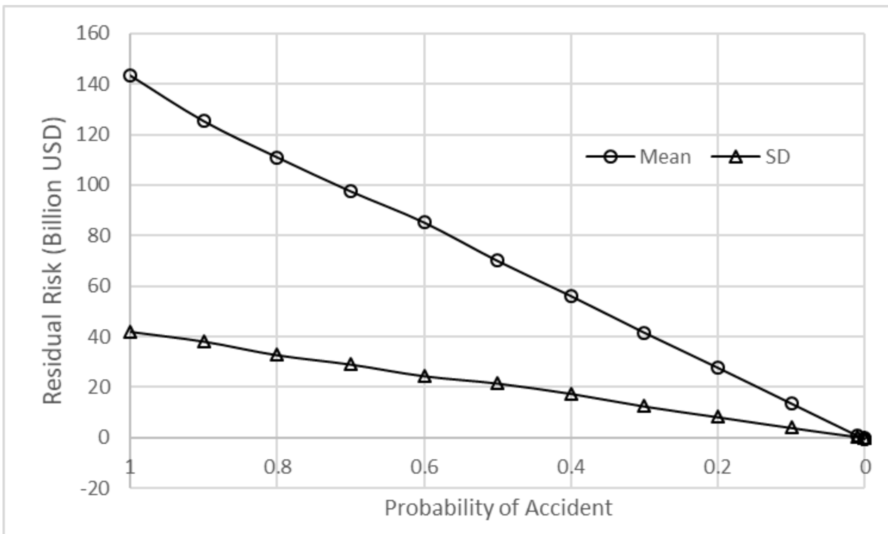

Figure 5.10: Mean and SD of residual risk vs probability of accident

5.4 Discussion

The study presents a methodology to analyze the economic costs and benefits of an ORC as a risk reduction measure for use in a remote harsh offshore environment. The capital cost and operational costs are determined based on comparable historic ship cost data. A high level approximation approach is adopted rather than a detailed analysis of construction or operating costs which is not practical at the present concept evaluation phase. However, the total estimated life-cycle cost of an ORC in this study is judged to be reasonable, comparing with similar sized and similarly complex ships.

In the second part, a loss curve is developed using the available data from previous blowout accidents. The total blowout costs, response time, offshore distance and other relevant details of these accidents are examined. These data are assumed to be normally distributed. However, several other distributions were tested during the study, and all distributions show a similar trend.

The limitation of the source data is a challenge. This includes both the ship cost data and the accident data. Thus this methodology proposes a probabilistic approach that shows 20% uncertainty in the predicted values. The process is repeated multiple times using the Monte Carlo simulation technique. The reduced logistical risk due to the ORC is indicated by the positive residual risk which is an unknown. The net benefit for installing an ORC is highly dependent on the probability of a blowout accident. Figure 5.11 shows the breakeven probability of 0.00365 for this case study. This is a relatively low probability but not nearly as low as the design probabilities for offshore system failures. The x-axis represents probability of negative residual risk in percentage. It is the percentage frequency of occurrence of the negative residual risk in the total number of simulations. The upper bound and lower bound probabilities are 0.01 and 0.001. Any probability value above 0.01 gives a positive return on investment from installing the

ORC and any value less than 0.001 would result in a negative return. This would mean that a net increase in safety has a net cost.

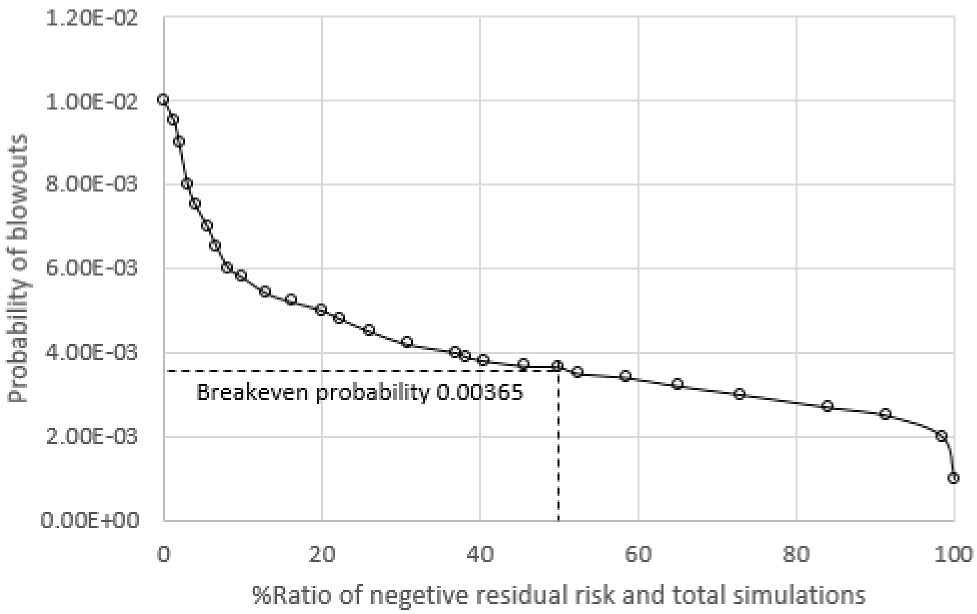

Figure 5.11: Sensitivity of blowout probability and residual risk

The emphasis of this study is to demonstrate the methodology and the numerical outputs are not absolute but based on reasonable estimates and available data. Also, the benefit of an ORC is only evaluated for one of its two main functions, emergency response and in this case for only one possible accident type. Another main objective of the ORC is providing helicopter landing facilities. Long flying distance is a major logistical challenge, which is associated with higher risk, especially in unfavorable environmental conditions.

It may be possible to use a similar methodology, to that employed here, to evaluate the additional net benefit associated with a reduction in flying distance. This is expected to be more challenging than the current case as a loss function associated with helicopter flying distance is expected to be more difficult to generate using historical data. This may in fact be superseded by a more simple analysis of helicopter range. If the platform is simply outside the safe range this would yield a simple comparison between the ORC concept and any available alternatives such as the use of existing intermediate production platforms or possibly an all-ship logistical support system. In either event, there are additional benefits associated with the other functions of the ORC that would be considered in a full analysis.

The ORC provides several additional benefits that are not risk reduction functions and thus not subject to the methodology presented here. For example the hotel function of the ORC provides temporary accommodation for inbound/outbound offshore personnel that may be useful for either aircraft operations or marine operations. Though this function is not a risk reduction objective, it offers an alternative crew transportation approach.

The study has set up a foundation for systematically analyzing the economic aspects of an ORC or any other form of technology based risk reduction initiatives. This approach can be expanded to include other functions or adapted for analyzing more complex scenarios such as, cost-benefit modeling of an ORC supporting more than one platform. The present study methodology can be applied to other types of offshore accidents such as fire, explosion, etc. For any given accident case, both probability and loss/consequence needs to be developed to get a complete risk profile. An offshore blowout was selected as a case study due to a relatively large data set of historical accidents and because the catastrophic nature of such accidents provides a very large potential loss that makes the case presented here easier to demonstrate.

5.5 Conclusions

The paper presents a probabilistic cost-benefit analysis method applied to the concept of an offshore resource centre in support of remote offshore operation. The methodology comprises estimating the total cost of ORC, developing loss model for blowout type accidents, determining the reduced loss as benefit, integrating cost-benefit models and uncertainty analysis. The proposed methodology and model provides:

- A basis for risk-based cost-benefit analysis that helps to assess the net financial cost or benefit of using a system such as an ORC as a risk reduction strategy for remote offshore developments.
- A structured but flexible approach that can be easily modified for different scenarios. Although this was developed for a particular system related to remote offshore developments, the same methods would apply to any potential risk mitigation system.
- A demonstration of the use of the Monte Carlo simulation technique, in a case where the historical data is sparse, to provide an output that demonstrates the

range of possible outcomes and thus a more credible output than deterministic modeling.

This methodology could be further improved if more data were available. However it is, in fact, preferable that accidents not occur, despite their value for studies such as this. Thus we sincerely hope that there are not any future additions to the available data on blowout accidents and we accept the limitations of this study as a benefit of a safer offshore industry. It would however be relatively easy to improve the ORC capital and operating cost information by performing a more detailed engineering feasibility study of the ORC concept.

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6. Summary, Conclusions and Future works

6.1 Summary

Remote offshore logistics support operations in harsh environmental conditions are challenging. Logistics challenges arise significantly from the two factors of extreme weather conditions and remoteness. The literature indicates that existing means of logistics support using helicopters or supply vessels alone may not be sufficient in far offshore operation in extreme environmental conditions. The risk modeling developed for this work identifies the most significant contributing factors to logistics challenges and the most effective risk reduction measures to mitigate these challenges. An intermediate offshore resource centre (ORC) is identified as an effective risk reduction measure and proposed as a supplement to conventional vessel and helicopter operations in order to mitigate the challenges, and an economic model is developed to analyze its practicability. This study identifies the unique challenges associated with this particular type of offshore development and proposes a solution to overcome these. Furthermore the work presents a means of analyzing the risk reduction effectiveness in economic terms. The outcomes of this research are summarized in the following.

Objective 1. To understand logistical risk in remote offshore operations

An advanced fault tree model is developed to perform risk analysis of offshore logistics operations. The inherent limitations of this model are identified. The model limitations are addressed by introducing unconventional logic gates. The data limitations are addressed by using both fuzzy logic-based and evidence-based approaches. The model provides more realistic results than the traditional fault tree model. The risk analysis suggests that marine logistics operations cannot respond sufficiently quickly in the case of an emergency on a distant platform. Helicopter operations are limited by the environmental conditions and flying range and aircraft capacity. This phase of the study identifies that new solutions are required to address this additional risk associated these challenges.

Objective 2. To identify effective risk reduction measures

Several alternate risk reduction measures to address logistical challenges identified in the first phase are evaluated. The BN model developed in this research is used to analyze the feasibility of each measure. This framework is applicable for a quantitative risk analysis for any given set of data. Two measures are found to be the highest ranked in terms of effectiveness in reducing the risk associated with distance and environment. These are the offshore refuge and an additional layer of safety equipment inventory.

Objective 3. To develop the concept of a viable solution

The concept developed as intermediate offshore resource centre (ORC) meets the purpose of a temporary refuge during emergencies and provides an emergency response asset for quicker reaction to an emergency scenario. The ORC also reduces risk associated with helicopter operations by reducing flying distance and by providing an intermediate landing point in case of emergency. The functional requirements of the ORC are set based on the example geographical location and the required capacity for supporting a single offshore platform. The methodology proposed for the concept development of the ORC can be used for any other case study or to develop a vessel or platform for supporting multiple offshore installations. Preliminary performance criteria such as ORC stability and station keeping in North Atlantic regions are also investigated to provide a concept level validation of the vessel.

Objective 4. To develop a framework to assess economic viability

In the final chapter this study develops a framework that can be used to determine whether an ORC, or any other risk reduction measure, is beneficial in economic terms by estimating risk reduction in economic terms and comparing this to the investment required in the risk reduction measure. The results in the present case indicate that the benefits of an ORC are significantly dependent on the assumed probability of a serious accident over the lifetime of the structure.

6.2 Technical Challenges and Limitations

The biggest challenge faced during this research is the scarcity of data on both operations in remote harsh regions and on the probability and consequences of major offshore accidents. This is mainly due to the fact there is simply not much experience with either. In the case of accidents, this is a good thing but it does make risk analysis and projections more difficult. Most of the data are collected from open literature. Some essential data for this study are not at all available. This is addressed either by logical assumption or expert elicitation. The case studies presented in this study are for demonstration purpose and provide clear indications of the logic and utility of the developed methods. However, care should be taken before using the actual numbers.

Apart from the data limitation, logistics support operation in a remote and harsh offshore environment is a complex process that involves many co-dependent factors. In general, risk modelling of such a process is a complicated task and often requires logical assumptions to address model-based limitations. This model can be further improved by incorporating experts' opinions from the offshore industry. Also, in this study, any factor/event in the risk model is considered to have binary states (pass/fail). However, multi-state factors can be considered in a more detailed modelling approach to represent a more practical scenario.

A literature review is performed to provide the perception of risk related to offshore helicopter operations. Although, detailed risk analysis of remote helicopter operations in extreme environments is not conducted in this study. A similar approach can be employed for helicopter risk analysis, though the required data is expected to be challenging to obtain.

The risk reduced by the ORC by enhancing helicopter operations is not analyzed in this study. Also, operating an ORC in remote and harsh offshore environments has its own risk elements. Further analysis would be required to gain a better understanding where all the risk elements of logistics support functions interlinked with shore base, ORC and production platform are considered in an integrated framework. Also, the role of standby vessels along with an ORC as a risk reduction measure could be evaluated.

Some of the technical uncertainties of the ORC such as motion analysis are also not performed as part of this study. The limitations of helicopter landing/take-off on the ORC imposed by weather or other technical issues should be evaluated in subsequent phases of the design spiral. Logistics transfer issues associated with rough weather conditions (e.g. high winds, waves, freezing rain) to/from a vessel and ORC also need to be further considered.

6.3 Recommendations and Future Work

Based on Based on some limitation of this work and on areas that could not be covered within the bounds of a single PhD study, the following future research work is recommended:

- The study presents a generic fault tree and BN model for a given case study. 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.

- Only discrete probabilities are used in the risk models. More robust estimation can be obtained if time-sensitive data can be used i.e. seasonal probability data. For example, the probability of some incidents such as the presence of iceberg, fog, etc. will vary over a year.

- Human error is considered as one parameter in this study, which could be a combination of a series of nodes that would represent different modes of human-related failure. With a more detailed literature review and practical datasets, the accuracy of this human error aspect can be further improved.
- The proposed ORC is in the concept development phase, which can be furthered by collecting more practical data and input from the industry and subsequently developing a further iteration on the design possibly through an engineering design study.

- The ORC concept is developed to minimize some of the challenges of logistics support operation to one oil production platform. In the case study, the space requirement and thus the overall dimensions of the ORC are estimated to meet the functional requirements for logistics supply to a single platform. However, the concept and the approach would remain the same for a design supporting multiple oil field operations. The space requirement can be determined using a similar approach presented in the case study based on the demand for multiple platforms. For example, if there are two platforms to support, more space will be required for in-transit personnel accommodation, service, fuel storage due to increased helicopter operations, etc. Indeed, the ORC could be more economical when it supports multiple platforms, although a detailed study is needed to confirm.

- The case study presented in this paper selected offshore Newfoundland to illustrate the concept development of an ORC. Some aspects of the concept are dictated by the geographical location, bathymetry and the physical environments. However, the basic requirements are dictated by the distance offshore for the production platform which is not site-specific. The environment is a somewhat lesser influence on the concept. For different environmental conditions such as the Gulf of Mexico or off Coast Brazil would need to be considered in a concept development that includes tropical storms and hurricanes, but no threat of dynamic ice or icebergs. Also, in deep water (> 500m), dynamic positioning (DP) could be the better option for station keeping. When the platform type and positioning system are defined, the modular concept development approach presented in the study can be implemented to determine the principal particulars of an ORC.

- In the cost-benefit analysis, the estimation of ORC capital and operating cost information by performing a more detailed engineering feasibility study. A more detail optimization problem can be solved considering multiple platforms and various accident scenarios.

- Some additional benefits of an ORC are not considered in the cost-benefit analysis presented here. The most significant additional risk reduction feature is the reduction of risk associated with long distance helicopter operations. The risk-based economic analysis may consider the reduced risk cost of long-distance helicopter operation associated with the ORC as an additional benefit to be compared with the required investment.

6.4 Conclusion

This study provides an analysis that identifies the major challenges of operating offshore installations in harsh northern regions at increased distances from shore based support. Although experience in this type of operation is currently very limited, developments that meet these criteria are under active consideration. This study presents an approach to risk analysis specifically adapted to the circumstances. A novel technological concept to mitigate the most significant identified risks is presented and validated in both technical and risk reduction terms. The method of comparing risk cost and investment provides a rational means of evaluating this or any other risk reduction approach. It is hoped that these ideas, methods and concepts will make a positive contribution to offshore safety as new developments are considered and implemented.