Analyzing Seasonal Effects on Logistical Risks Associated with Servicing an Oil Production Facility in the Flemish Pass

by

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A thesis submitted to the

School of Graduate Studies

in partial fulfillment of the requirements for the degree of

Master of Applied Science in Oil and Gas Engineering

Faculty of Engineering and Applied Science

Memorial University of Newfoundland

February 2022

St. John's Newfoundland and Labrador

ABSTRACT

There are field discoveries in the oil and gas industry that require significant investment to develop, and the Bay du Nord and Baccalieu fields in the Flemish Pass are no exception. Long-distance, deep-water production facilities are expected to increase marine logistical risks in an area that already is known for its harsh weather conditions, and the implications of not properly understanding and mitigating these risks are the safety of those involved in the operations and millions of dollars in material damage.

This research is focused on more accurately modelling the seasonal effects of changing environmental conditions on the failure rate of marine logistics operations. This work is an extension of previous research in the field and is focused on further model development and refinement. Fault tree and Bayesian network models are compared, with applicable data uncertainty considerations. Model refinements to reflect conditional dependencies more accurately, and a process for establishing mitigation efforts and accident prevention strategies are then proposed. This thesis details data acquisition, application of seasonal conditions inputs, and a quantitative technique for analyzing pre-emptive barriers to logistics operation failure. The final product is a strategy for estimation of logistics operation failures

ACKNOWLEDGMENTS

I would first like to express my gratitude to my supervisor, Dr. Faisal Khan, for both his assistance and guidance during the completion of this thesis, and for instilling an interest in safety and risk engineering during my undergraduate studies at Memorial University. This early interest provided me with an understanding of safety and risk assessment principles that were immediately useful beginning my career in the nuclear power generation industry and lead me to return to Memorial University and pursue a master's degree in the subject. This thesis would not have been possible without his patience, wisdom, and support. In addition, I would like to thank Dr. Imtiaz for his support throughout and input on my thesis.

I would also like to acknowledge my friends and family who have supported me through my educational pursuits in a variety of ways; from their words of encouragement, assistance with relocation moving back and forth between Ontario and Newfoundland, and all the help they have provided throughout every obstacle I have encountered in my journey. Having a support network of this magnitude is a privilege that has allowed me to succeed where many others do not even have the opportunity.

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Chapter 1 Introduction

1.1 General

Large field discoveries have been made in exploratory wells in the Flemish Pass Basin as depicted in Figure 1-1 below. The Bay du Nord, Bay de Verde, and Baccalieu discovery wells contain an estimated three hundred million barrels (Equinor, 2021). In addition, there have been several other well discoveries in the Flemish pass, including the Harpoon and Mizzen fields.

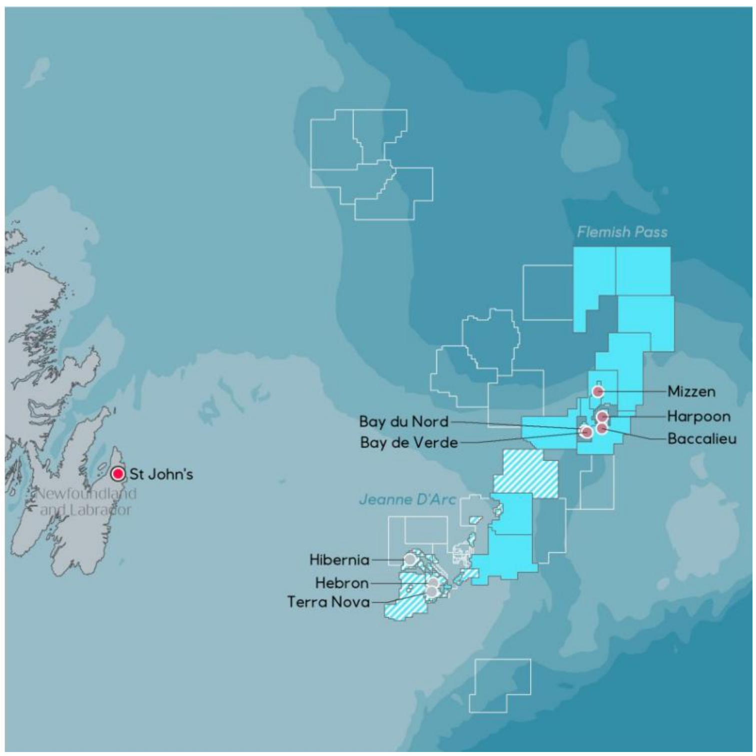

Figure 1-1 Location of Bay du Nord Discover (Equinor, 2021)

This is an exciting discovery for the oil industry in Newfoundland and Labrador, but there are significant challenges that will need to be addressed before a production facility is up and running. The current development concept is to operate and service a floating production storage and offloading (FPSO) approximately 500km east of the coast of Newfoundland and in water depths of approximately 1,200m (Equinor, 2021). One of the major challenges that will need to be addressed is the increased safety risk to logistical operations which arise when servicing an operation this far offshore. The wind, wave, and ice conditions off the coast of Newfoundland in the Grand Banks area are dangerous, and to extend out to the Flemish Pass means both a further distance travelled through dangerous waters, and an increased risk while in those areas.

Offshore oil and gas production facilities are already operational in waters within 250km of the Flemish Pass, but environmental data presented in this thesis suggest that even within proximity of the area, there are significant variations in expected conditions.

Currently, most crews are transported to oil production facilities off the coast of Newfoundland via helicopter. This provides the advantage of being able to transport personnel quickly, as well as being able to transport equipment or personnel in an emergency. The significant challenges that arise from supporting a platform further away from the coast, such as in the Flemish Pass, are:

- An increase in travel time which inherently increase the safety risk due to the exposure period.
- Refueling challenges.
- Response time during an emergency scenario.

The Bay du Nord is within range of the fuel tank limitations of industry available helicopters such as the Sikorsky S-92A; however because of the wind conditions expected 500km offshore, if a helicopter were unable to land, there would be limited fuel to proceed with a safe landing at a different location, making helicopter travel a significant risk.

A potential production facility near the Flemish Pass would rely heavily on logistics operations planned with large marine vessels. While these vessels are built to withstand regular travel in the Atlantic Ocean, vessel design does not mitigate all risks associated with the logistics operation. The C-Core (2015) report presents a high-level quantitative comparison of various regions in the Atlantic Ocean through what is referred to as the Fleming-Drover Harshness Index.

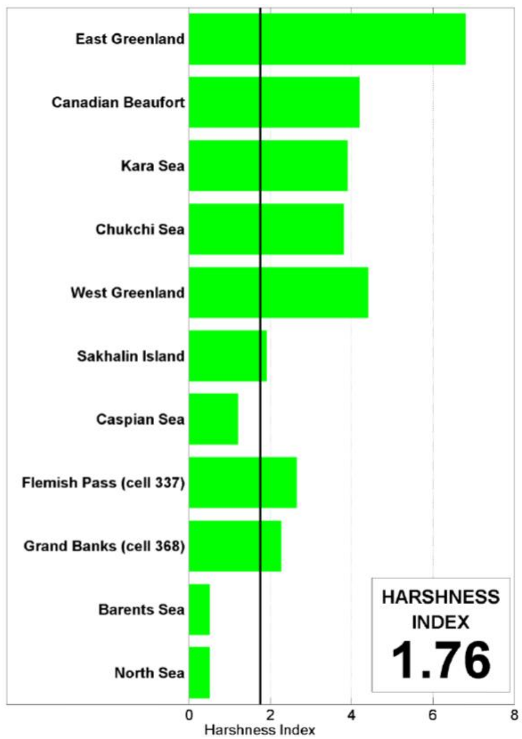

Figure 1-2 Fleming-Drover Harshness Index (C-Core, 2015)

The Harshness Index was developed to provide a single, easy to understand parameter that represents the degree of harshness of expected environmental conditions. It is calculated considering days of excessive sea ice concentration, open water iceberg density, and consistency of high significant wave heights. While it is not a perfect parameter for quantitatively assessing the increased risk to Marine logistics operations, it does provide insight into the relative risk increase to expect. The harshness index near the Flemish Pass is 33% higher than that of the Grand Banks, as depicted in Figure 1-2.

This research is being pursued to understand the marine logistics operation risks more extensively and analyze what level of variation in risk to expect throughout the year. Wind and subsequent wave conditions are a concern during a longer extent of the year than iceberg or sea ice conditions in this region, as depicted in Figure 1-3. This expected to have considerable effects on the expected failure rates of a marine logistics operation.

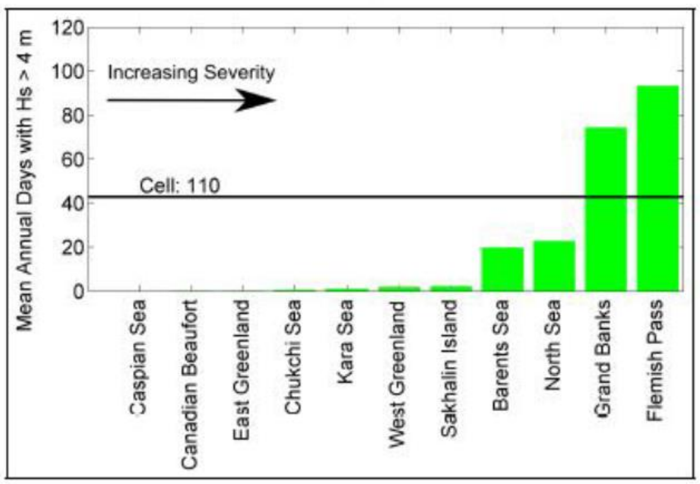

Figure 1-3 Operation Failure Risk Increase due to Significant Wave Heights (C-Core, 2015)

Additionally, the current body of research pertaining to accident modelling has been focused on analysis of an accident model with respect to minimizing failure rates based on expected costs of failure outcomes. This thesis will aim to expand qualitative accident prevention evaluation and option selection. This will be achieved by focusing on identifying the capital expenditures required to reduce failure rates most efficiently with seasonal changes incorporated in the model.

1.2 Overall Objectives of This Research

There are significant logistical risks for marine operations servicing the Flemish Pass area; Hibernia and the FPSO SeaRose already face these challenges. For example, if waves exceed a certain threshold height, the sea conditions are not considered safe to load/offload, and logistical operations are delayed, or accidents occur. The increased wave heights recorded in the Flemish Pass make overcoming this challenge a complex problem (C-Core, 2015).

The goal of this thesis is to quantitatively understand the increased risks to development in this area, and to review modelling techniques for analyzing safety and risk to logistical operations. It will demonstrate methods for modelling accident and delay scenarios as they are applied to logistics operations, discuss how both model and data uncertainty impacts can be mitigated, and create a logistics operation failure scenario model which incorporates the seasonal changes and risk conditions when operating off the coast of Newfoundland and Labrador. While the marine conditions are considered relatively harsh, they do vary significantly throughout the year; ice, wind, wave, and visibility conditions all change dramatically in this location month over month, as this study will illustrate. Accident modelling has a long history in Safety and Risk Engineering, and there have been many different models used to quantify the safety risk. This thesis will use these methods and principles to outline and compare models, consider the time-sensitivity of basic events through the incorporation of seasonal data, of a marine logistics operation scenario that would be required if a production facility were to be made operational in the Flemish Pass. Finally, with a refined logistics operation failure model established, a proposed method for quantitative analysis of mitigation strategies and accident prevention options is presented.

1.3 Overview of the Present Research

This research is intended to cover the gap of seasonal effects on a logistics operation, such as the fault tree model proposed by Rahman et al. (2019) and the subsequent conditional dependence-based model by Rahman et al. (2020). The models presented in this study are also intended to be applicable for any marine logistics operation servicing a remote location and can be tailored to any location with the appropriate environmental data.

The attractiveness of a Bayesian network model is the ability to model interdependencies and conditional dependencies that exist between basic and intermediate nodes. Fault trees simply do not have the flexibility to properly model the complex relationships between varying environmental effects and other aspects of a marine logistics operation, and this research aims to further illuminate that. Time-sensitive prior probabilities are considered for a complete comparison between a fault tree model and a Bayesian network model, and the advantages of developing a fault tree model prior to network model refinement are demonstrated.

In this research we considered several critical changes to traditional marine logistics operation modelling and analysis. These are:

- Consideration of time-sensitive prior probabilities to increase base model accuracy of both fault tree and Bayesian Network Models
- Refinement of the interdependencies between environmental conditions to align with current research on the relationships between various environmental impacts.
- Proposal of a quantitative method for evaluation and budgetary prioritization of barriers and solutions available to reduce marine logistics operation failure rates utilizing a ratio of estimated risk reduction and annualized capital expenditures.

This revised modelling approach is a key step in quantitatively understanding the increased risks between different areas of the Atlantic Ocean as they relate to accident models. It also highlights the variation in failure rate changes that can be expected seasonally in a specific area so that mitigation strategies and accident prevention techniques can be prioritized accordingly.

1.4 Thesis Structure

A brief description of the background information that motivated this research is given in Chapter 1 followed by a thorough literature review specific to this research in Chapter 2. The research methodology is depicted in Chapter 3. The results of the final analysis and model refinement have been discussed in Chapter 4, followed by conclusions and recommendations for future research to advance the state-of-the-art in Chapter 5.

The supporting documents and materials have been appended to this thesis, detailing the fault tree model assessment in Appendix A, uncertainty analysis using triangular fuzzy numbers in Appendix B, and posterior probability analysis for the proposed Bayesian networks in Appendix C.

Chapter 2 Literature Review

2.1 Accident Modelling Methods

Accident modelling is a primary part of safety engineering and risk management. The simplest of these models are sequential accident models. These models attempt to describe an accident as a failure of a sequence of events or compiling factors, after an initiating event occurs. This initiating event can be a result of numerous different causes, from an unsafe act to human error, or failure of a component or system.

One of the early forms of accident modelling was “Domino Theory” proposed by Heinrich as early as 1929 (Disaster Management Institute, 2021). Figure 2-1 describes this model. It theorizes that accidents can be viewed as a causal chain of events, each failing one after another like cascading dominos.

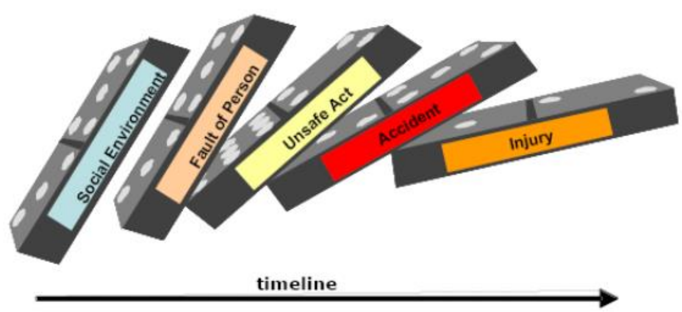

Figure 2-1 The Domino Theory (Disaster Management Institute, 2021)

Epidemiological models introduced barriers of failures, such as in the “Swiss Cheese Model,” proposed by Reason (1990), but were still sequential in nature. As seen in Figure 2-2, it models an accident as a performance deviation, which can then propagate through barriers given the right combination of factors of the performance deviation and success capability of each barrier.

These models consider the propagation of an accident to occur in the same manner as the spread of a disease or virus.

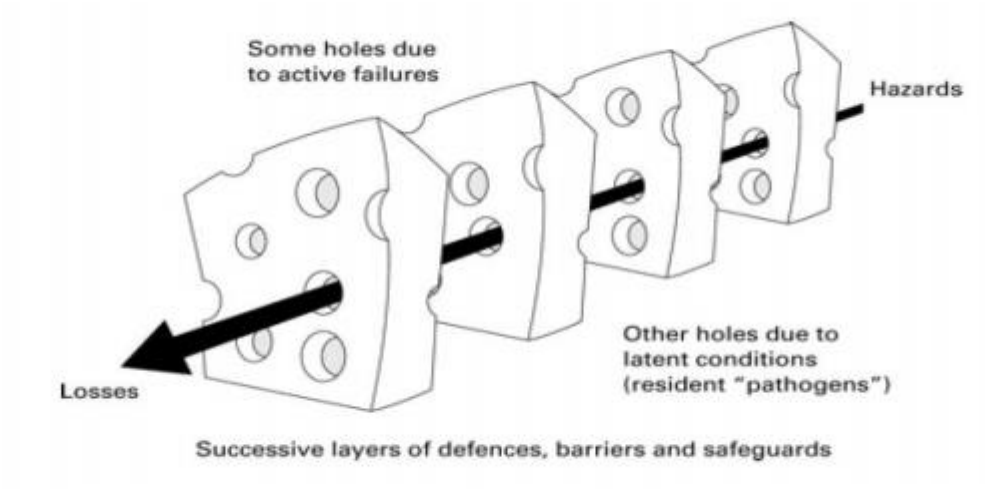

Figure 2-2 Reason's Swiss Cheese Model (Henriksen et al., 2008)

There have been multiple other models presented that have had a variety of focus areas in industry, but they are descriptive models, and not predictive. The System Hazard identification, prediction, and prevention (SHIPP) methodology is a modern accident modelling method which is predictive. While this model was developed for the primary use of process accidents, the application can be tuned to model most accident scenarios – barriers just need to be changed to match the focus area.

The SHIPP methodology is a process that involves system definition and hazard identification (Rathnayaka, Khan, & Amyotte, 2011) and analyzing the failure of barriers as described from Figure 2-3 below for the process industry. It is typically accompanied by a fault tree analysis outlining the details of each barrier failure.

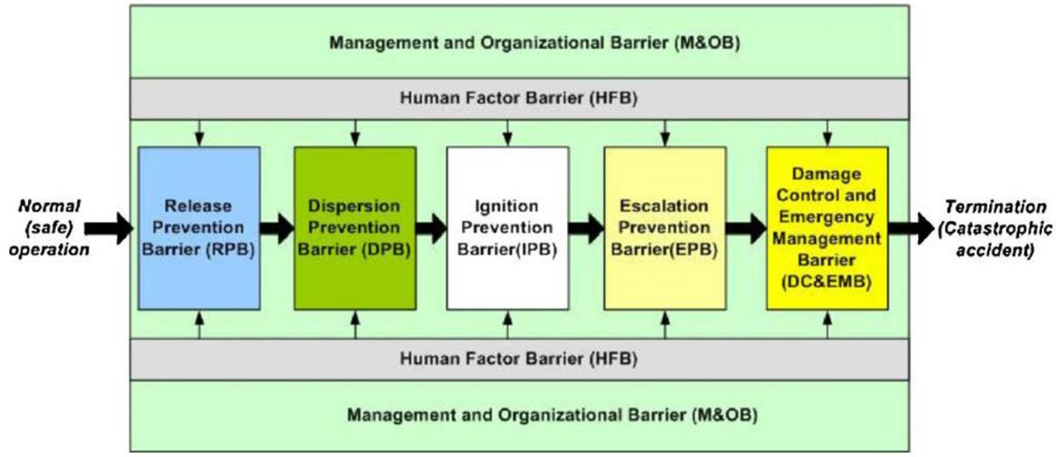

Figure 2-3 SHIPP Methodology Barriers (Rathnayaka et al., 2011)

Accident sequences are still linearly considered in this model. Each outcome is linked to the failure of a specific barrier success or failure. For example, the breakdown of the Release Prevention Barrier would result in the Dispersion barrier taking effect; if that barrier is a success the resulting outcome could be classified as a "Near Miss." This model is comprehensive and works well to model process accidents, as these accidents typically do follow a linear pattern with Human Factors and Management and Organizational Barriers playing a role throughout the development of an accident scenario. This approach has been successfully used to model and analyze process accidents such as the Macondo well blowout from BP's Deepwater Horizon (Rathnayaka, Khan & Amyotte, 2013).

Fault tree-based risk models are often used to model and analyze accident scenarios. Fault tree models are sequential accident models used to determine the probability of an event. In safety and risk accident modelling, the top-level event usually represents an accident state, or failure scenario (Lewis, 1994). The sequential nature of the fault tree analysis presents similar shortcomings to other sequential accident models, such as difficulty representing interdependencies between basic or intermediate events.

Basic fault trees used for accident modelling use AND gates and OR gates commonly to represent the relationship between events in a fault tree. An AND gate is used when events interact in parallel structure, and failure of the resultant intermediate and top event requires failure of both input events in parallel. The failure probability of the resultant event is calculated by Equation (1) in this scenario. An OR gate is used when events interact in series structure, and failure of any event linked in series leads to failure of the resultant intermediate or top event. The failure probability of the resultant event in this scenario is represented by Equation (2), where P_i is the failure probability of the indicated event identified by i (Adedigba, Khan &Yang, 2016)

$$P_{AND} = \prod_{i=1}^{n} P_i \tag{1}$$

$$P_{OR} = 1 - \prod_{i=1}^{n} (1 - P_i) \tag{2}$$

The Boolean algebra conducted to quantitatively analyze gate relationships of events in a fault tree model leads to top event probability calculation, given probabilities of basic events. A qualitative analysis of the fault tree model can be completed by analyzing its minimal cut sets (MCS). MCS is a set of a minimum number of events that produces the top event if and only if events of the set occur, and analyzing these sets is a method of identifying critical factors or events in a fault tree model. Minimal cut sets have been studied extensively with Boolean logic operators and algorithms (Jane, Lin & Yuan, 1993) and simulations. Monte Carlo simulations have been used to identify critical factors in reliability engineering (Lin & Donaghey, 1993).

There are approaches used to relax the rigid model assumptions, such as adding inhibit gates to account for interdependencies (Rahman et al., 2019), but it is preferable to refine these relationships in a Bayesian Network as there is much more flexible to refine and update the model when new information or data is collected on basic events.

A Bayesian network model is an example of a network-based approach for predictive accident modelling. This method of modelling can be transposed from the SHIPP model or other fault tree model. Essentially, the methodology states that there are real life scenarios where end events used in the SHIPP methodology can escalate in any order, and not only through sequential hierarchy (Baksh, Khan, Gadag & Ferdous, 2015). In these scenarios, a network is built exemplifying the interdependencies of events.

A fault tree is still a useful tool to map out an accident model and can be converted to a simple Bayesian network that can be further refined (Khakzad, Khan & Amyotte, 2011). In Figure 2-4, this mapping process is demonstrated.

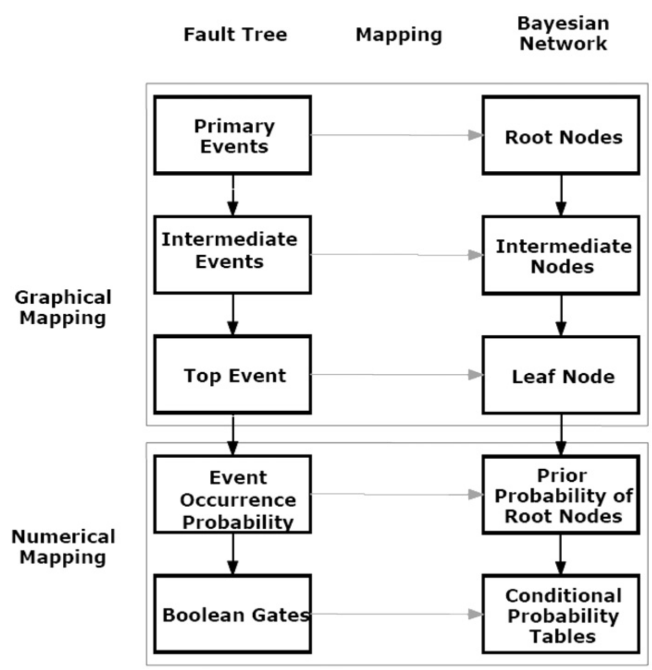

Figure 2-4 Mapping a Fault Tree to a Bayesian Network (Khakzad et al., 2011).

Conditional probability tables are first developed into binary tables dependent on fault tree gates. Further refinement of event interdependencies can be made after initial mapping of a fault tree model to a Bayesian network. The conditional probability tables must also be updated after the network is refined. Based on both the conditional probabilities and the chain rule, the network represents the joint probability distribution *P(U)* of a set of discrete random variables U = $\{A_1, ..., A_n\}$. This is represented through the network by Equation (3):

$$P(U) = \prod_{i=1}^{n} P\left(A_i \middle| P_{a(A_i)}\right) \tag{3}$$

where $P_{a(A_i)}$ is the parent of variable A_i and *P(U)* is the joint probability distribution of variables (Jensen & Nielsen, 2001; Pearl, 2014)

Some refinement can be represented in the Fault Tree Model through use of Noisy-OR and leaky Noisy-OR gates to address binary states of a typical OR gate product. Inhibit gates are used to address conditional dependencies in this case (Oniśko, Druzdzel &Wasyluk, 2001). A Noisy-OR gate is used to describe the interaction between several causes and their common effect. In a simple example, a binary Noisy-OR gate is applied where there are several possible causes of failure, X_1, X_2, …, X_n lead to a common effect *Y* where each of the causes has a probability of being sufficient to produce the effect in the absence of all other causes. In addition, it must be assumed that the ability of each cause to be sufficient is independent of the presence of other causes.

In some cases, an extension of Noisy-OR gates theory is required to capture situations where the common effect *Y* can manifest without assumed causal triggers. This extended model is a leaky Noisy-OR gate (Henrion, 1987). If the Noisy-OR gate model does not capture all possible causes of Y, an additional parameter called the “leak probability” is introduced to account for unmodelled causes. Effectively, the parameter reflects the probability of the intermediate event occurring spontaneously.

A Bayesian approach also allows updating of the prior probabilities through analyzing intermediate node outcome scenarios when evidence is available. Posterior probabilities can be calculated, and probabilities updated as evidence is applied to the model through:

$$P(U|E) = \frac{P(U,E)}{P(E)} = \frac{P(U,E)}{\sum_U P(U,E)} \tag{4}$$

This gives a significant advantage to the Bayesian modelling approach as updating probabilities through posterior probability analysis inherently helps mitigate concerns of data uncertainty.

2.2 Data Uncertainty and Seasonal Effects

2.2.1 Uncertainty mitigation strategies

One of the major concerns in accident modelling is the probability inputs of basic events. As noted previously, in a Bayesian network event probabilities can be updated given evidence utilizing Eq. (4). The accuracy of the basic event prior probability, however, will help to improve accuracy of the model, and the model would produce even more accurate results for outcome nodes of interest with evidence updating. In a practical industry setting, model accuracy would be desired in an optimized timeline, and having a base model that converges on high confidence levels of results would be desirable.

In much of the research on accident and delay modelling, data uncertainty techniques are utilised to mitigate concerns of basic probability accuracy, such as evidence theory (Ferdous, Khan, Sadiq, Amyotte & Veitch, 2011; Limbourg et al., 2007) or fuzzy set theory (Ferdous, Khan, Veitch & Amyotte, 2009; Mamood, Ahmadi, Verma, Srividya & Kumar, 2013; Miri Lavasani, Wang, Yang & Finlay, 2011; Pan & Yun, 1997; Rahman et al., 2019; Tanaka, 1983). These techniques have demonstrably improved the quality of outputs in the model and are useful tools for properly applying probabilistic inputs that are vague or incomplete.

Evidence Theory, commonly known as Dempster-Shafer Theory, was first proposed by Dempster (1966), and was later extended by Shafer (1976). It is applied to address incomplete and missing data, in addition to incorporating experts' opinions in the analysis where basic event probabilities may be in question, and expert opinion is required. It is also useful for determining appropriate probability inputs for basic events where conflicting expert opinions are available.

The theory of fuzzy sets was first put forward by Zadeh, Klir & Yuan (1996) in 1965; it proposes ways of determining prior probabilities where vagueness or ambiguity exists in the data available. Even with reliable data sets, it is often challenging to determine the exact probabilities of specific events. In any case, fuzzy set theory was proposed to analyze inputs and obtain more precise input data (Zadeh, Klir & Yuan, 1996).

The fuzzy set theory states that a fuzzy set is characterized through varying degrees ranging from 0 to 1 of a membership function (μ). The fuzzy set then represents the relationship between a membership function and the event probability. The degree of membership of element *x* in the fuzzy set of an event *p* is mathematically expressed as (Ross, 2004):

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

Fuzzy numbers take many forms; however triangular and trapezoidal fuzzy numbers have been typically used when analyzing reliability data or performing risk assessments (Ferdous et al., 2011). When triangular fuzzy numbers are used, the fuzzy sets are determined by different α- cut values and are determined using Equation (5) below (Ferdous et al., 2011; Pan & Yun, 1997).

$$p_{\alpha} = [p_{\mathrm{l}} + \alpha(p_m - p_{\mathrm{l}}), p_{\mathrm{u}} - \alpha(p_{\mathrm{u}} - p_{\mathrm{m}})] \tag{5}$$

Where p_l, p_m, and p_u represent the minimum, most likely, and upper maximum values respectively in the α- cut level. Figure 2-5 below represents this graphically.

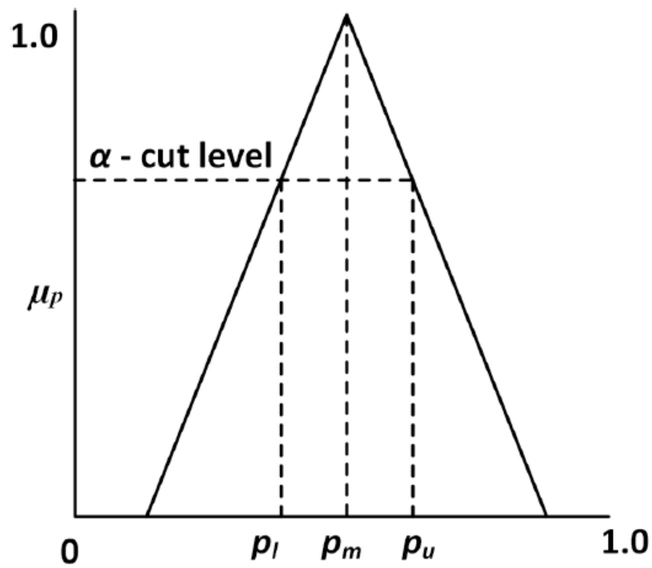

Figure 2-5 Triangular Fuzzy Event Graphical Representation (Rahman et al., 2019)

For fault tree analysis, after fuzzy probabilities are calculated for basic events at set α- cut levels, the top event fuzzified failure probability must be estimated, and then defuzzification of that failure probability is required to produce the final failure probability. The equations for outcome probabilities of traditional AND and OR gates seen in fault trees are rewritten in Eq. (6) and Eq. (7) respectively below when fuzzy sets are incorporated.

$$p_l^{\alpha} = \prod_{i=1}^{n} p_{il}^{\alpha} \; ; \; p_u^{\alpha} = \prod_{i=1}^{n} p_{iu}^{\alpha} \tag{6}$$

$$p_l^{\alpha} = 1 - \prod_{i=1}^{n}(1 - p_{il}^{\alpha}) \; ; \; p_u^{\alpha} = 1 - \prod_{i=1}^{n}(1 - p_{iu}^{\alpha}) \tag{7}$$

There have been multiple methods proposed for defuzzification. The centre of area or center of gravity method is commonly used, and other methods are available such as the centre of maxima and weighted average have been presented (Klir & Yuan, 1995). More recently two step methods have emerged, such as proposed by Román-Flores, Chalco-Cano $ Figueroa-Garcia (2020) for type-2 fuzzy interval defuzzification.

2.2.2 Time Sensitive Probabilities

To accurately model failure modes of logistics operations, event probabilities must be variable, as environmental conditions, especially those off the coast of Newfoundland and Labrador, vary from one extreme to the other throughout the course of a year. This is true of not only ice conditions like iceberg density, pack ice and sea ice concentration, and marine icing, but also of wind, wave, and fog conditions, which all have varying degrees of effects on marine operations of any sort.

A comprehensive study of the physical oceanography off the coast of Newfoundland was completed by C-Core (2015). In this study, the harshness index is outlined by area, or cell as referenced in the study, and analyzed comparatively. A map of each of the cells is shown in Figure 2-6. This study allows both analysis of the Flemish Pass environmental conditions, and comparisons to conditions for existing marine logistics operations where delay scenarios and accident conditions are less of an unknown, like those operations servicing the Hibernia gravity-based structure (GBS) platform or the floating production storage and offloading (FPSO) SeaRose.

The harshness index as described in Section 1.1 presented in the C-Core (2015) report is designed as a benchmark parameter two quantitatively compare environments based on three factors:

- Mean annual number of days with a sea ice concentration greater than six tenths (C_6)

- Mean annual number of days with a significant wave height greater than four meters (H_{S4})
- Mean annual open-water iceberg density (AD).

The harshness index (HI) is described through Equation (8) and (9). This thesis will consider other factors contributing to the risk of marine logistics operations, and the relationships between these factors and the factors considered when using the harshness index for quantitative assessment.

$$HI = \frac{6(C_6)}{350} + \frac{2.5(H_{S4})}{110} + 1.5[12 + 2\log_{10}(AD)] \quad \text{for AD} \geq 10^{-6}\ \text{km}^{-2} \tag{8}$$

$$HI = \frac{6(C_6)}{350} + \frac{2.5(H_{S4})}{110} \quad \text{for AD} < 10^{-6}\ \text{km}^{-2} \tag{9}$$

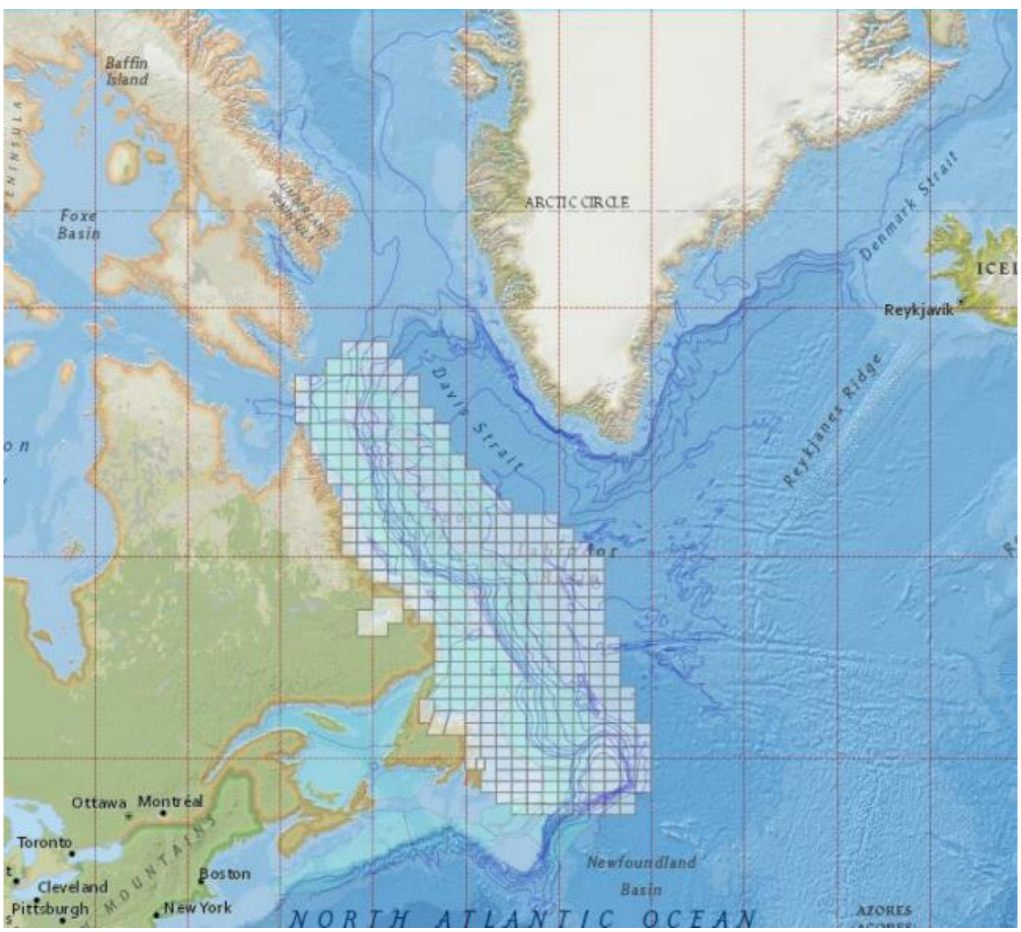

Figure 2-6 Cell Layout of the C-Core Physical Oceanography Study (C-Core, 2015)

The study produced a detailed report on each cell and an annual analysis of wind, waves, currents, visibility, icing, pack ice, and icebergs. In addition, it provided a comparison report with other key regions in the study. This study provided a key contribution to recent probabilistic risk assessment research with respect to environmental conditions; a time phased range of outcomes based on month or season. Data are available for significant wave heights, wind speeds, icebergs and icing conditions, and visibility probabilities.

Assumptions are required on what extremity of environmental conditions results in a “failure” and can be updated with expert opinion or evidence in a network-based model, as exceeding an exact threshold for a specific environmental condition is not an accurate representation of how marine logistic operations are delayed or how accidents occur.

There have also been icebergs surveys completed by the U.S. Coast Guard each day that can also be used to analyze iceberg density and estimate probabilities of iceberg-related incidents through considering relative vessel proximity (U.S. Coast Guard Navigation Center, 2015). Each latitude and longitude have an iceberg count associated with it that is updated daily, as shown in Figure 2-7, the location of the Flemish pass area as a focal point of this thesis is shown and combining Iceberg count with average iceberg size would indicate the probability of iceberg proximity in the area.

Additionally, this research conducted annually by the U.S Coast Guard illuminates the changes in iceberg flows from year to year, adding a layer of uncertainty to any basic event probability concerning icebergs, even when considering the data is time sensitive annually.

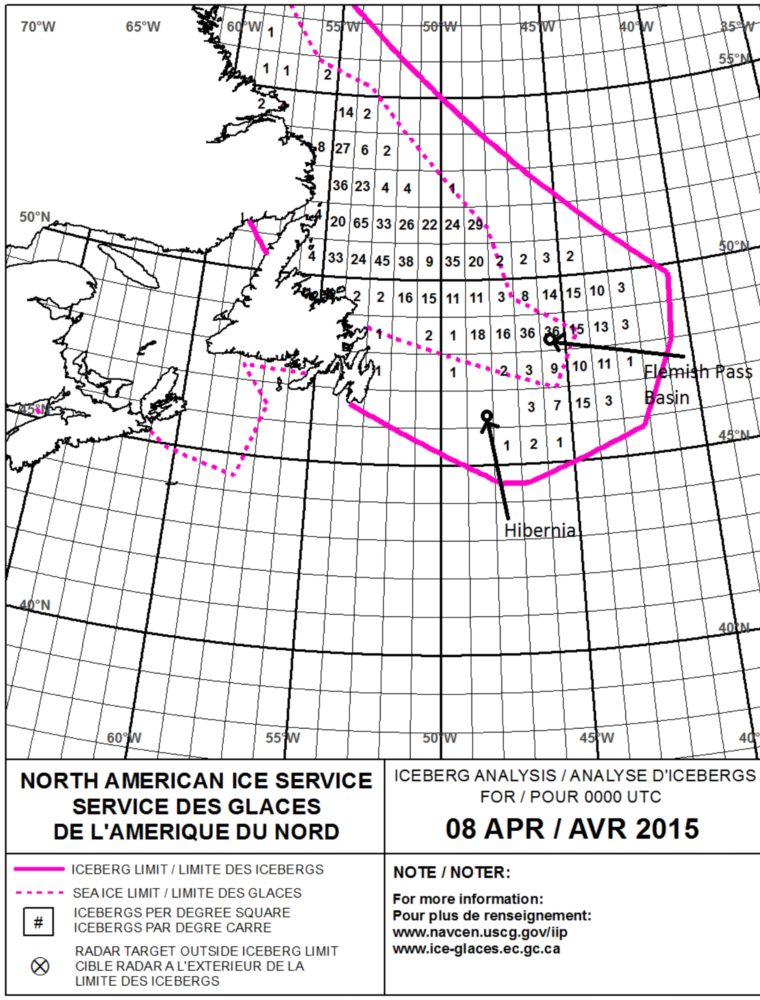

Figure 2-7 Iceberg Count by Day in the Atlantic Ocean (U.S. Coast Guard Navigation Center, 2015)

These time sensitive seasonal effects as they pertain to basic probability inputs in Bayesian networks are not widely studied, though there has been recent research conducted which considers time phased outputs for accident modelling of a liquefied natural gas (LNG) plant (Baksh et al., 2015). The basic event probabilities for models that do consider variables such as ice, wind and wave conditions have demonstrated their considerable impact on model outcomes. A comprehensive study on emergency marine logistics operations has been completed by Rahman et al. (2019), as an example, but is limited by discrete probability data that are not time sensitive. In this study, prior to implementing mitigating factors, when evidence is set that emergency response failure has occur, environmental conditions show failure rates 48% of the time, with ice conditions being a major causal factor when considering basic event impacts.

From the base model, these environmental condition prior probability inputs could be updated utilizing evidence of environmental conditions to obtain posterior probabilities. However, given the comprehensive studying of physical oceanography off the coast of Newfoundland and Labrador and subsequent results, this study will aim to more accurately model time sensitive environmental conditions.

Accident modelling for marine operations is an academic focus area within the province of Newfoundland and Labrador, given the safety challenges presented both in the oil and gas industry and by the harsh sea conditions (Afenyo, Khan, Veitch & Yang, 2017; Rahman et al., 2019). Through this research and other research globally, a plethora of marine transport scenarios have been considered, and as such, many of the other basic events which can be assumed are not time sensitive can have input probabilities assigned.

Chapter 3 Research Methodology

3.1 Methodology Summary

At a high level the methodology used to develop the models will be similar to that used by Rahman et al., (2019) and Rahman et al., (2020) for the fault tree and Bayesian Network models, respectively. First key contributing factors will be identified through layout of a typical operation. A fault tree will then be develop based on the identified relationships between basic events discussed through the logistics operation diagram.

The next step will differ from previous research, while some of the non-time sensitive probabilities will be cited from previous research, the environmental conditions, or time sensitive data, will be acquired through rigorous review of the physical oceanography. Data acquisition of this nature will aim to identify changing basic event inputs that are time-phased monthly throughout the year.

Finally, after analysis of the fault tree model and consideration of data uncertainty, using the process outlined in Figure 2-4, the fault tree will be mapped to a Bayesian Network, so that the model can be refined and mitigation strategies can be demonstrated to be analyzed quantitatively.

3.2 Identification of Contributing Factors

To construct a model for the delay of a logistics operation, a flow diagram of the basic events leading to a successful operation has been constructed and illustrated in Figure 3-1. The subset of contributing factors outlining failure modes for each phase of operation is also illustrated.

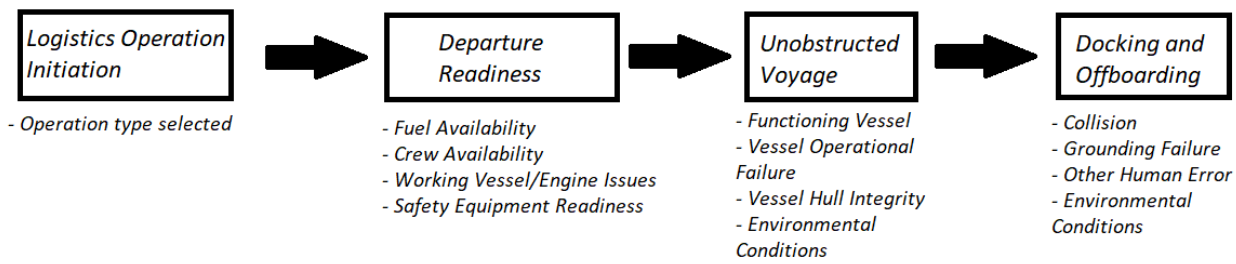

Figure 3-1 Logistics Operation Diagram

To define a logistics operation for the purpose of this study, any operation with the intention to transport supplies, material, or personnel to or from a potential production facility within the Flemish pass off the coast of Newfoundland has been considered. This would include emergency support personnel that would be tasked with assistance in the recovery from hazardous incidents (Rahman et al., 2019). If any of the higher-level phases of the operation outlined in Figure 3-1 fail, the operation overall will be affected. This could either lead to logistics support delays, or in the case of an emergency response operation, lead to unmitigated hazards for prolonged periods resulting in an escalating safety situation. Each of the phases of the successful logistics operation is discussed below, with key factors that contribute to their success or failure identified.

3.2.1 Logistics Operation Initiation

This represents the basic initiation phase of logistics. The concept as a phase requires further development but an additional extension of this research could further outline the failure mode changes associated with different operations in one network. For instance, while individuals involved are highly trained in an emergency response situation, the very nature of emergency response operations can correlate to increased frequency of incidents, or more specifically human error, due to time constraints or overbearing hazards. Human reliability assessment during offshore emergency conditions has been analyzed by Musharraf et al. (2013), and the likelihood of mishaps in the human reliability analysis models presented are magnitudes higher than human error failure estimations used in recent research (Afenyo et al., 2017).

3.2.2 Departure Readiness

Failure to depart within scheduled time will lead to delays in a marine logistics operation, or a prolonged event in the case of an emergency response operation. One constraint is fuel availability for the operation and engine or propulsion functionality. Another major consideration here would be crew and equipment availability; if crew are delayed or unavailable for external reasons, or there is a lack of safety equipment, the operation would be halted or fail. Many of the root causes for marine logistics accidents have been researched by Kum & Sahin (2015). Rahman et al. (2019) outlines vessel equipment requirements required for safe and successful operation; lifesaving appliances, firefighting equipment, and navigation equipment.

3.2.3 Unobstructed Voyage

After a successful departure and unobstructed voyage with equipment functioning for the duration are the next key requirements for a successful logistics operation. Environmental factors such as wind, waves, and ice conditions including pack ice, icebergs, and marine icing, can all greatly impact the journey of a vessel. The time sensitive nature of the environmental conditions is hypothesized to impact the concern level of delays due to these factors and should be reflected in the model as evidence of failures is applied in months where environmental conditions are at their least severe.

In addition to environmental conditions, an unobstructed voyage requires vessel hull integrity and proper navigation. Navigational systems and other operation and communications controls systems have been studied extensively in a marine transportation environment (Kristiansen, 2013).

For the purposes of this study, promptness is defined as success of both the departure phase and voyage, marking the event that the vessel has safely arrived. One of the benefits of modelling a logistics operation through a Bayesian network is that occurrences where resultant outcome intermediate events, such as promptness, can be modelled such that are not solely dependent on "OR" or "AND" gate logic. For example, there are scenarios where prompt arrival of a vessel can still be achieved if the departure or voyage is delayed only a brief period. From a planning perspective, there is a contingency allotted for operation planning, and while the goal will always be the highest levels of efficiency, practically speaking, small delays can and do occur whilst the resultant overall operation remains a success from the perspective of overall timing and safety metrics.

3.2.4 Docking and Offboarding

Upon prompt arrival of the vessel, there is a final phase of the logistics operation before it can be a deemed a success. Depending on the operation, this will usually involve docking, and offloading cargo or personnel, or in the case of an emergency operation, safety equipment and response teams. Failure modes considered are environmental conditions and specific failures such as grounding the vessel, vessel impact or collisions, and human errors that are present.

Grounding and collision errors that could result in a breach of the hull during marine logistics have been discussed by Ronza, Carol, Espejo, Vilchez & Arnaldos (2006) for bulk transport of hydrocarbons. This study focuses on initiating events of a tanker breach when approaching or leaving berth, manoeuvring, or while completing loading or offloading processes. Many of the events such as ship to ship collisions from passing ships during tanker charging would not be applicable at even the low frequencies outlined in this study due to the remoteness of the potential operation in the Flemish Pass, however grounding and collisions must be considered as an operation failure event, as marine logistics operations operate from site to site. So, while grounding may not be a high concern in the Flemish Pass, it can be a concern on a loaded tanker heading to shore.

Finally, an accident model would not be complete without the consideration of human error. Human error has been studied extensively, including mitigation and prevention techniques (Senders & Moray, 2020), and incidents analyzed logistics operation failure indicate it a significant risk during offloading and throughout a rescue operation. Human error is better characterized in a network-based model such as a Bayesian network, as it affects all phases of the operation.

3.3 Fault Tree Logistics Risk Model

A fault tree is developed to perform a quantitative analysis for each phase of the operation. "Logistics Operation Failure" is considered the top event and primary causes are defined by basic events, connected by logic gates. In this model basic events have binary inputs, success and failure, and in the fault tree models are basic events are considered mutually independent (Khakzad et al., 2011). A fault tree is constructed to reflect causes of the top event, but only includes the most credible faults, as assessed by the analysts of the situation and model constructors. The fault tree may not represent all possible system failure causes (Vesely, Goldberg, Roberts & Haasl, 1981).

The logistics operation phases have been discussed and a simple fault tree model can be depicted as a result in Figures 3-2 through to Figure 3-4. The logistics operation failure is made up of promptness and the docking and offloading. Promptness is defined as a successful departure and an unobstructed voyage, and each of these components are broken down into intermediate event failures and basic event failures as identified.

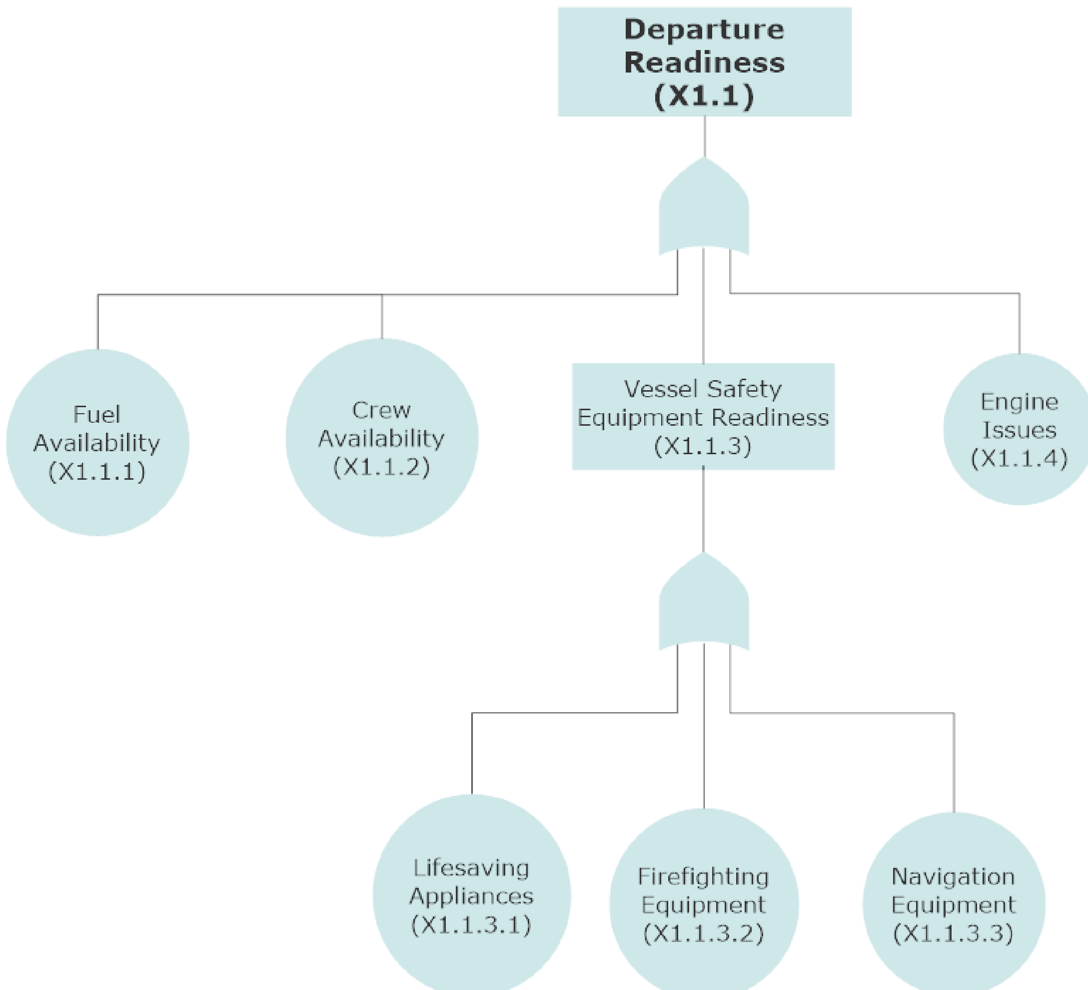

Figure 3-2 Fault Tree Model for Departure Readiness

After constructing a fault tree model, its outcomes can be analyzed quantitatively and qualitatively. Quantitatively, the system can be analyzed simply through Equation (6) and

Equation (7) representing the system Boolean logic to determine top-level event failure probability. Qualitatively, the model minimal cut sets can be reviewed; in this case the basic and intermediate events are all connected by OR-gates. Since all the basic events in the fault trees are connected by OR-gates, failure of any event can result in a logistics operation failure so minimal cut sets will not be an effective way to identify critical factors.

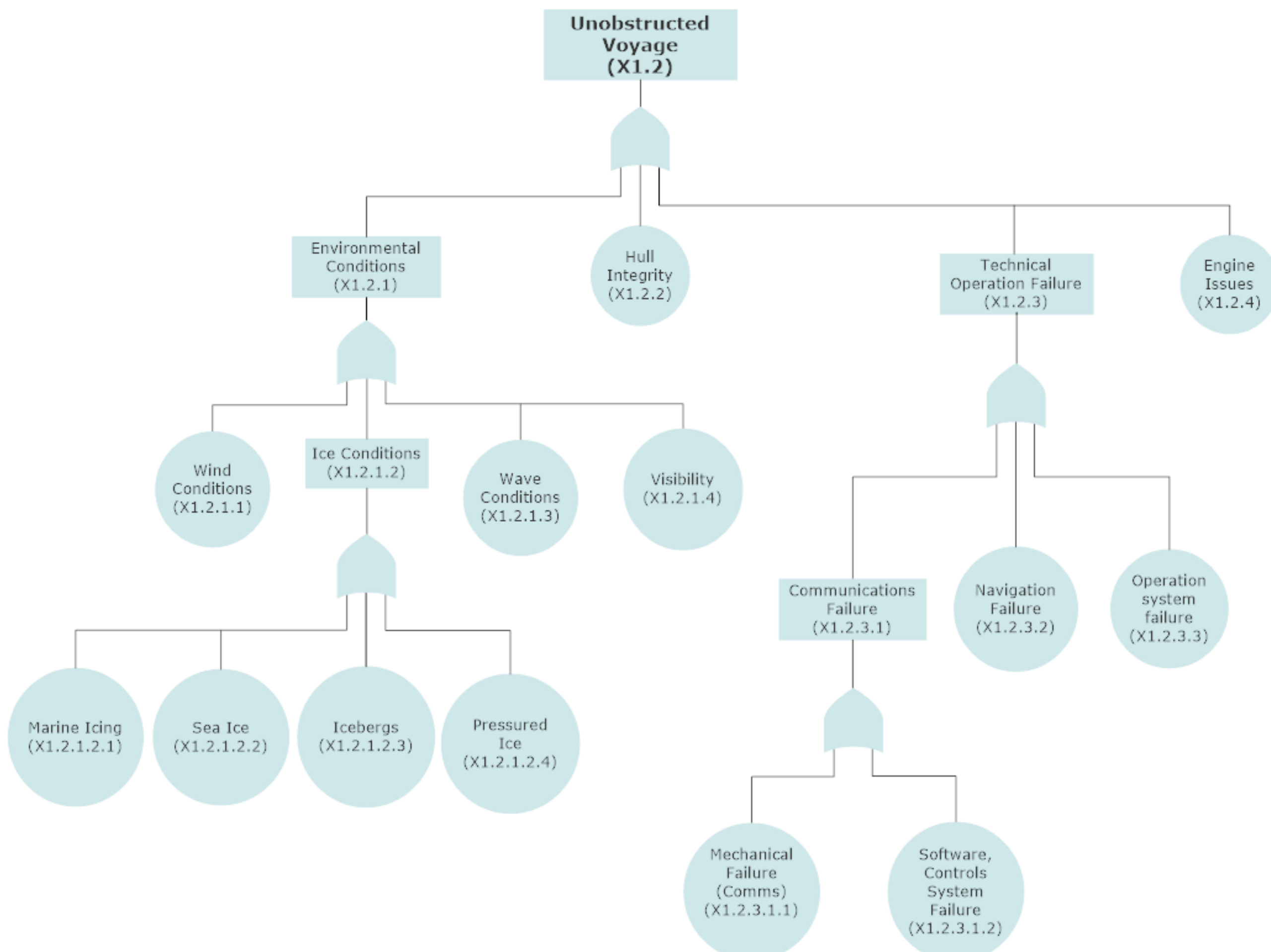

Figure 3-3 Fault Tree Model for Unobstructed Voyage

Environmental conditions have been repeated as both a failure mode of offloading and docking and an unobstructed voyage; in a fault tree they must be considered as separate intermediate events but even considered as time sensitive events, there is obvious correlation between failure of an operation due to environmental conditions in all phases of the operation, given all phases of the operation would occur within approximately 500 km of one another. These dependencies are more easily documented and addressed in a network model.

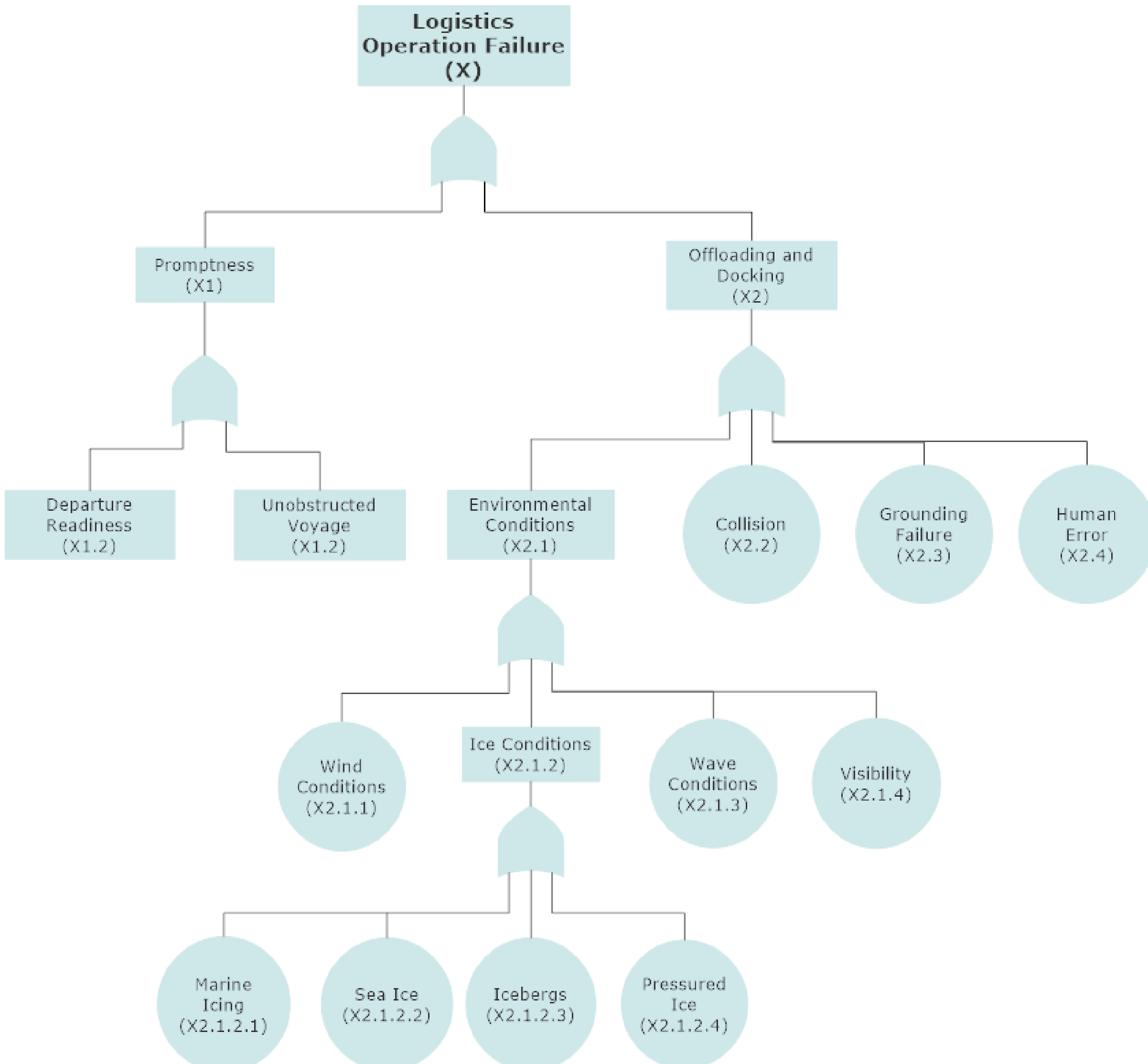

Figure 3-4 Fault Tree Model for Logistics Operation Failure

3.4 Basic Event Prior Probabilities

3.4.1 Basic Events Which Are Not Time Sensitive

To perform a quantitative analysis of the fault tree model proposed, all basic events must have assigned prior probabilities. The basic event prior probability inputs which are not time sensitive outlined in Table 3-1 have been sourced from the body of research on marine logistics and safety and reliability engineering outlined in the literature review of this study. These inputs are all subject to data uncertainty concerns.

Table 3-1 Failure Probabilities of Basic Events which are not Time Sensitive

Identifier	Basic Event	Probability of Failure	Citation
X1.1.1	Fuel Availability	3.97E-04	(Kum & Sahin 2015)
X1.1.2	Crew Availability	3.97E-04	(Kum & Sahin 2015)
X1.1.3.1	Lifesaving Appliances	1.00E-03	(Bercha 2003)
X1.1.3.2	Firefighting Equipment	3.97E-04	(Kum & Sahin 2015)
X1.1.3.3	Navigation Equipment	2.55E-03	(Antao & Soares 2006)
X1.1.4, X1.2.4	Engine Issues	2.60E-04	(Kum & Sahin 2015)
X1.2.2	Hull Integrity	1.33E-04	(Christou & Konstantinidou, 2012)
X1.2.3.1.1	Mechanical Failure (Comms)	1.00E-05	(Bercha 2003)
X1.2.3.1.2	Software, Controls System Failure	4.00E-04	(Afenyo et al., 2017)
X1.2.3.2	Navigation Failure	2.00E-06	(Amrozowicz, Brown & Golay, 1997)
X1.2.3.3	Operation System Failure	1.00E-04	(Afenyo et al., 2017)
X2.2	Collision	2.20E-03	(Ronzo, 2006)
X2.3	Grounding Failure	3.00E-05	(Ronzo, 2006)
X2.4	Human Error	3.00E-04	(Afenyo et al., 2017)

3.4.2 Basic Events Which Are Time Sensitive

The remaining basic events outlined in the fault tree model not documented in Table 3-1 are considered time sensitive. The intent of data acquisition supporting this thesis is to outline these time sensitive basic events and document data acquisition techniques to further support the level of data uncertainty that can be assumed when quantitatively analyzing the logistics operation failure models.

3.4.2.1 Wind Conditions

Wind conditions are a key element of why the logistics operations in the grand banks, and proposed operations in the Flemish Pass, fall prey to harsh environmental conditions. As documented in previous research, wind speeds effect much of the other environmental dangers such as marine icing and wave heights.

The primary source for the wind data is the Meteorological Service of Canada (MSC) 50 North Atlantic Wave Hindcast (MSC50) data set. The MSC50 is a hindcast wind and wave data set for Atlantic Canadian waters prepared for Environment Canada (C-Core, 2015). The data set being analyzed contains either hourly or three-hour interval recordings of wind and wave values for sixty years from 1954 to 2013. The resultant probabilities of wind speeds exceeding certain thresholds is then calculated and shown in Table 3-2.

Table 3-2 Probability of Exceeding Threshold Wind Speeds (C-Core, 2015)

Cell: 349 47.75°N 46.5°W	Wind Speed - Probability of Exceedance by Month											
Wind Speed (m/s)	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2	1	1	0.999	0.998	0.991	0.992	0.988	0.995	0.996	0.998	1	0.999
4	0.991	0.991	0.975	0.961	0.923	0.915	0.894	0.92	0.95	0.975	0.983	0.987
6	0.951	0.949	0.912	0.852	0.782	0.74	0.701	0.729	0.813	0.891	0.916	0.94
8	0.869	0.859	0.803	0.69	0.58	0.512	0.457	0.479	0.622	0.748	0.794	0.847
10	0.751	0.734	0.656	0.499	0.373	0.294	0.22	0.254	0.417	0.57	0.629	0.719
12	0.602	0.581	0.489	0.319	0.199	0.141	0.076	0.111	0.234	0.385	0.454	0.561
14	0.437	0.416	0.323	0.18	0.092	0.053	0.023	0.04	0.115	0.224	0.293	0.403
16	0.283	0.257	0.191	0.089	0.037	0.016	0.006	0.012	0.051	0.106	0.165	0.251
18	0.161	0.143	0.088	0.037	0.013	0.003	0.001	0.005	0.021	0.043	0.08	0.133
20	0.08	0.073	0.035	0.014	0.004	0.001	0	0.001	0.008	0.018	0.032	0.061
22	0.035	0.036	0.013	0.005	0.001	0	0	0	0.003	0.007	0.011	0.026
24	0.014	0.017	0.004	0.001	0	0	0	0	0.002	0.003	0.005	0.01
26	0.004	0.007	0.001	0	0	0	0	0	0	0.001	0.001	0.005
28	0.001	0.002	0	0	0	0	0	0	0	0	0	0.002
30	0	0.001	0	0	0	0	0	0	0	0	0	0.001
32	0	0	0	0	0	0	0	0	0	0	0	0

For the purposes of this study, with a success or failure binary outcome, a threshold limit must be chosen by which it is considered that a marine logistics operation would be delayed, or otherwise fail if already in progress, due to a significant safety event. This assumption applies to all environmental conditions listed in this chapter and could be altered accordingly in a network model to represent a specific scenario more accurately, or a specific vessel. Considering a scenario where the significant delay and rescheduling of a marine logistics operation would be enough to classify the operation intent as a failure, it is assumed that the winds exceeding 24 m/s (86.4 km/h) would be sufficient to significantly increase risk of impact to the operation. Winds in range of 80 km/h are sourced as having delayed large vessel operations or cause significant risk of accidents during voyage and docking maneuvers, in the Atlantic Ocean, such as passenger or cargo ferry operation (CBC News, 2009). The annually time sensitive input probabilities then are presented in Table 3-3. Note that assumptions related to threshold limits are considered when reviewing data uncertainty and mitigating concerns. Data uncertainty would be of lower levels when a specific operation is being considered and evidence is used to modify the threshold assumptions.

Table 3-3 Annual Basic Event Probability Inputs for Wind Conditions

Month	**Input Probability**
January	1.40E-02
February	1.70E-02
March	4.00E-03
April	1.00E-03
May	0
June	0
July	0
August	0
September	2.00E-03
October	3.00E-03
November	5.00E-03
December	1.00E-02

In future studies including the time sensitive nature of environmental conditions, it would be valuable to define environmental factors not as binary success or failure outcomes but by a severity scale such as mild, moderate, severe, and extreme. Extremes over decades, as shown in Table 3-4, could be used to create a rating mechanism by which environmental conditions could be characterized more accurately to allow for better risk assessments of executing any given marine operation.

Table 3-4 Wind Speed Extremes in the Flemish Pass (C-Core, 2015)

Cell: 349 47.75°N 46.5°W		Wind Speed Extremes by Return Period												
		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual
WS (m/s)	10 Year	27.6	28.6	25.9	23.4	21.4	18.9	17.2	21.3	24.4	25	25.5	28.2	30.2
	25 Year	29.1	30.1	27.8	25.4	23.3	20	18.3	24.4	26.9	27.2	27.1	30.2	31.4
	50 Year	30.3	31.2	29.3	27	24.7	20.9	19	26.9	28.9	29	28.4	31.8	32.3
	100 Yr.	31.5	32.2	30.8	28.7	26.2	21.7	19.8	29.4	30.8	30.7	29.6	33.3	33.1

3.4.2.2 Wave Conditions

The hazards presented to ships are numerous and the structural integrity of vessels operating at sea are of utmost concern when considering both accident prevention and minimizing costly maintenance and capital expenditures. Material fatigue due to wave loading on marine transport vessels has been studied extensively (Temarel et al., 2016). Alongside these material concerns, a vessel capsizing, or marine icing caused from sea spray, are additional concerns if an untimely logistics operation proceeds. Significant wave height, typically denoted by H_s, is a commonly used metric for representing sea-state severity. It is defined as the average wave height, from trough to crest, of the highest third of waves, or commonly as four times the square root of the variance in sea surface elevation (Thomson & Rogers, 2014)

Wind and wave conditions in the Flemish Pass are of even more serious concern for marine vessels when compared to other regions in the grand banks and off the coast of Newfoundland. According to recent reports, regional trends show the substantial highest significant wave height values on the grand banks increasing going out into the Flemish Pass and the Flemish Cap. The estimated 100-year return period significant wave height was found to be in the range of 17.0m to 18.0m in the Flemish Pass area (C-Core, p.2-6, 2015). This represents 16% higher wave heights during extreme conditions when compared to waters surrounding the nearby Hibernia gravity-based structure.

Table 3-5 Annual Data Summary for Significant Wave Heights in the Flemish Pass (C-Core, 2015)

Cell: 349 47.75°N 46.5°W		Summary Table - Wave												
		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual
Sig. Wave Height (m)	Mean	4.6	4.4	3.7	3.1	2.4	2.1	1.8	1.9	2.6	3.3	3.7	4.4	3.2
	St. Dev.	1.9	1.9	1.6	1.3	1	0.8	0.7	0.8	1.2	1.4	1.6	1.8	1.7
	Median	4.3	4	3.5	2.8	2.2	1.9	1.7	1.8	2.4	3	3.4	4	2.8
	P90	7	6.7	5.8	4.8	3.7	3.1	2.6	2.9	4	5	5.8	6.7	5.3
	Max.	14	15.5	13.3	11	11.7	10.8	7.2	8.8	13.5	12.9	13.1	15.3	15.5
	Dom. Dir.	295	265	325	225	225	225	225	225	235	325	315	315	225

Wave data collected through the Meteorological Service of Canada (MSC) 50 North Atlantic Wave Hindcast (MSC50) data set is presented in the C-Core (2015) report similarly to the results for wind speeds. The standard deviation, mean, and median significant wave height for the region are shown in Table 3-5, along with the 90th percentile, maximum and most frequent or dominant direction of the waves.

The probability of significant wave heights exceeding the annual average of 3.2 m in the Flemish Pass changes seasonally. As shown in Table 3-6, in January, the probability of wave heights exceeding 4m is greater than 5E-1, decreasing to 1.3E-2 in July, given wind speeds directly affect significant wave heights, the same trend of seasonal change is to be expected, and the drastic changes in both parameters throughout the year should result in significantly improved logistics operation efficiency in July and August, and provide opportunities to explore the next most effective mitigation barriers.

Table 3-6 Probability of Exceeding Threshold Significant Wave Height Levels (C-Core, 2015)

Cell: 349 47.75°N 46.5°W		Significant Wave Height - Probability of Exceedance by Month											
		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Sig. Wave Height (m)	1	1	0.999	0.978	0.995	0.989	0.971	0.95	0.961	0.994	1	0.999	1
	2	0.985	0.963	0.911	0.828	0.603	0.442	0.308	0.369	0.673	0.865	0.911	0.972
	3	0.848	0.786	0.647	0.444	0.221	0.122	0.054	0.092	0.278	0.505	0.62	0.793
	4	0.567	0.501	0.371	0.196	0.074	0.03	0.013	0.024	0.105	0.236	0.35	0.512
	5	0.331	0.276	0.185	0.083	0.027	0.009	0.003	0.008	0.042	0.099	0.174	0.293
	6	0.179	0.151	0.084	0.035	0.01	0.002	0	0.003	0.021	0.042	0.084	0.158
	7	0.098	0.086	0.038	0.014	0.004	0.001	0	0.001	0.011	0.022	0.043	0.083
	8	0.062	0.053	0.021	0.007	0.002	0	0	0	0.005	0.013	0.023	0.05
	9	0.038	0.033	0.009	0.003	0.001	0	0	0	0.003	0.008	0.013	0.031
	10	0.021	0.019	0.003	0.001	0	0	0	0	0.002	0.005	0.006	0.015
	11	0.011	0.009	0.001	0	0	0	0	0	0.001	0.002	0.002	0.007
	12	0.004	0.004	0	0	0	0	0	0	0	0.001	0.001	0.003
	13	0.001	0.002	0	0	0	0	0	0	0	0	0	0.001
	14	0	0	0	0	0	0	0	0	0	0	0	0
	15	0	0	0	0	0	0	0	0	0	0	0	0
	16	0	0	0	0	0	0	0	0	0	0	0	0

To provide initial basic event inputs, an assumption is required on what threshold of significant wave height constitutes a failure. It is important to note when considering significant wave heights that they represent a mean value and that waves higher than the recorded significant wave height, up to 50 to 100% higher, can and should be expected if planning for a safe voyage (Thomson & Rogers, 2014). For the purposes of this study, the probability of exceeding 11m to 12m significant wave height will be considered for initial inputs and are tabulated below in Table 3-7. These prior probability inputs will be used for network modelling prior to evidence updating and are corroborated by inputs used in recent related research (Rahman et al., 2020).

Table 3-7 Annual Basic Event Probability Inputs for Wave Conditions

Month	Input Probability
January	4.00E-03
February	4.00E-03
March	1.00E-03
April	0
May	0
June	0
July	0
August	0
September	1.00E-03
October	1.00E-03
November	1.00E-03
December	3.00E-03

3.4.2.3 Marine Icing

Rahman et al. (2020) presents a scenario that when evidence of failure was set for an emergency response logistics operation, environmental conditions were a contributing factor at 48% failure prior to implementing mitigating factors. However, the leading casual factors of the "environmental conditions" intermediate event shown in the model, ice conditions, are only problematic during a short time annually. Analysis of time sensitive factors would be required to show through application of mitigation costs where it would be more prudent to spend capital on mitigation strategies.

Of these ice conditions, marine icing is a common occurrence in northern ocean areas, and it is most frequently caused by seawater spray and offshore precipitation. Icing on a ship as shown in Figure 3-5 can lead to substantial issues during a logistics operation, such as stability of the vessel or hazardous safety conditions for the crew (Dehghani-Sanij, Dehghani, Naterer & Muzychka, 2017). Additionally, when icing becomes severe, it can significantly impact a vessel’s weight, subsequently changing its design parameters and leading to much lower vessel stability.

Figure 3-5 Extreme Marine Icing Scenario (Cammaert, 2013)

To summarize the seasonal changes in icing conditions, the C-Core (2015) report uses a predictive icing model developed by Overland, Pease, Preisendorfer & Comiskey (1986), and later calibrated by Overland (1990). An icing predictor is used as an analogue of the expected icing rate and icing risk class, divided into the following classifications:

- No Icing
- Light Icing
- Moderate Icing
- Heavy Icing
- Extreme Icing

The predictor index (PR) is a simple formula shown in Equation (10),

$$PR = \frac{V_a(T_f - T_a)}{1 + 0.4(T_w - T_f)} \tag{10}$$

where V_a is the wind speed, T_f is the freezing point of the seawater, T_w is the sea temperature, and T_a is the air temperature. The PR is calculated based on these parameters daily and the average distribution annually, as shown in Figure 3-6. A PR between 0 and 22 indicates that icing rates will be light, or less than 7.0E-1 cm/hr, while a PR of greater than 83 is indicative of extreme icing, corresponding to an icing rate of about 4.0 cm/hr.

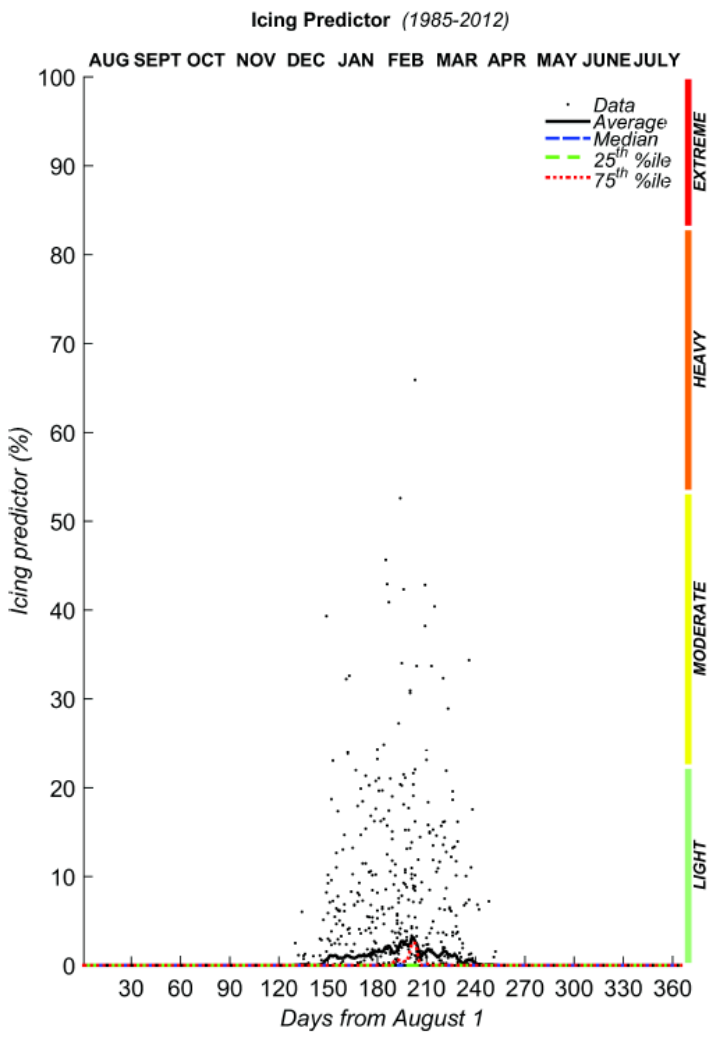

Figure 3-6 Annual Marine Icing Event Predictor in the Flemish Pass

It is important to note that the marine icing, when described by Equation (10) above, is solely dependant on the surrounding seawater and air temperature and wind speeds. In a Bayesian network model, it will be possible to better model and approximate this relationship and fully understand the true contributing causal factors to failure due to environmental conditions.

As the event results in this fault tree model are binary, either event failure or event success, an initial assumption is made that $1/100^{th}$ of the time PR is greater than 22 the basic event will result in failure. In other words, probability input is 0.01 x $P_{PR>22}$, where $P_{PR>22}$ is the probability icing conditions are more severe than light icing denoted by greater than 7.0E-1 cm/hr accumulation rate. This is a conservative assumption supported by historical events of documented marine icing incidents and expert opinions solicited from recent research and accident modelling (Rahman et al., 2019, Rahman et al., 2020). Time sensitive initial inputs used are shown in Table 3-8 based on the above assumption.

Table 3-8 Annual Basic Event Probability Inputs for Marine Icing Conditions

Month	**Input Probability**
January	6.67E-04
February	1.69E-03
March	1.69E-03
April	3.23E-04
May	0
June	0
July	0
August	0
September	0
October	0
November	0
December	1.61E-04

3.4.2.4 Sea Ice

Sea Ice presents a few challenges for marine logistics, especially when considering significant delays as a failure scenario. Firstly, the sea ice poses a danger to the integrity of the ships' components, even when manageable. Vessel components making consistent contact with the ice rapidly increases the fatigue of materials and can result in untimely maintenance, costly repairs, or accident scenarios if a failure occurs during vessel operation. In addition to these material concerns, delays can be simply due to the presence of significant sea ice, as the most common method of mitigating material damage and fatigue due to ice contact is to engage in an icebreaking operation with an appropriately designed specific vessel (Riska, 2011). Even with access to icebreaking ships in a fleet, operations can be significantly delayed due to rerouting while ice-breaking operations are undertaken, or even halted in severe icing conditions.

Sea Ice conditions in the Flemish Pass have been analyzed by C-Core (2015), with inputs derived from ice charts archived by the Canadian Ice Service (CIS) and National Ice Center (NIC). This study divides sea ice into four categories; no ice, open water, concentration greater than or equal to one tenth, and concentration greater than or equal to six tenths, defining "open water" as the condition where there is sea ice present, but it is of concentrations below one tenth of the area. "Old ice" is defined in the C-Core (2015) report as ice that has survived a previous melt season. Old ice is a specific concern because it consequently has snow build-up on the ice, creating scenarios where pressurized ice can much more easily trap a vessel, and significantly impact the efficiency of ice-breaking operations (Sturm & Massom, 2009). This would signify that pack ice has developed in the area and presents a significant risk. The probability distribution over the cell area is presented each month, the distribution in March is shown in Figure 3-7 as an example.

The report shows the concentration of any sea ice buildup and the probability of old ice over the reporting period noted.

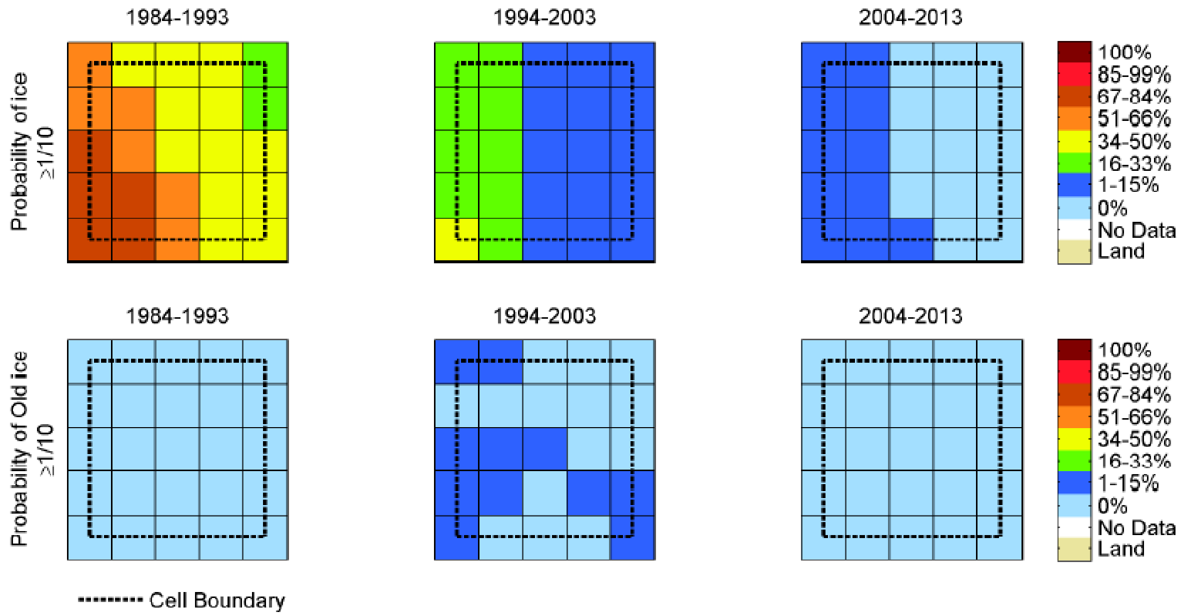

Figure 3-7 March Sea Ice Conditions in the Flemish Pass (C-Core, 2015)

It is noteworthy that the probability of any sea ice concentration being greater than 1.0E-1 changes throughout the reporting period. The probability of the concentration of sea ice being higher than 1.0E-1 between 1984 and 1993 was 50 to 100% higher throughout the cell region than between 1994 and 2003, and a similar decrease in sea ice concentration is noted in the last reported period, from 2004 and 2013. For the purposes of time sensitive basic event probability inputs, an average across the reporting periods is used. Recent research is being conducted on what vessel routing opportunities become available in the Atlantic and Artic Oceans given the receding sea ice conditions (Stevenson, Davies, Huntington & Sheard, 2019).

Table 3-9 Probabilities of Encountering Sea Ice of Different Varieties (C-Core, 2015)

Cell: 349 47.75°N 46.5°W	Pack Ice: Probability of encounter											
	All Ice ≥1/10			All Ice ≥6/10			Old Ice ≥1/10			Old Ice ≥6/10		
	1984-1993	1994-2003	2004-2013	1984-1993	1994-2003	2004-2013	1984-1993	1994-2003	2004-2013	1984-1993	1994-2003	2004-2013
January	0.4	0	0	0.1	0	0	0	0	0	0	0	0
February	0.9	0.3	0	0.6	0.1	0	0	0	0	0	0	0
March	0.8	0.4	0.1	0.5	0.2	0.1	0	0.1	0	0	0	0
April	0.5	0.2	0.2	0.2	0.2	0.1	0	0.1	0	0	0	0
May	0.1	0	0.1	0	0	0	0	0	0	0	0	0
June	0	0	0	0	0	0	0	0	0	0	0	0
July	0	0	0	0	0	0	0	0	0	0	0	0
August	0	0	0	0	0	0	0	0	0	0	0	0
September	0	0	0	0	0	0	0	0	0	0	0	0
October	0	0	0	0	0	0	0	0	0	0	0	0
November	0	0	0	0	0	0	0	0	0	0	0	0
December	0	0	0	0	0	0	0	0	0	0	0	0

Sea Ice basic event initial input probability requires an assumption on what conditions constitutes binary success or failure. The average probability of sea ice concentration exceeding 1.0E-1 was used as shown in Table 3-9, and an initial assumption of 5% failure occurrence during any time ice concentration is encountered equal to or greater than 1.0E-1. This is a conservative assumption and time sensitive initial inputs resultant as depicted in Table 3-10 are supported by recent research (Kum & Sahin, 2015).

Table 3-10 Annual Basic Event Probability Inputs for Failure due to Sea Ice

Month	**Input Probability**
January	6.67E-04
February	2.00E-02
March	2.17E-02
April	1.50E-02
May	3.33E-03
June	0
July	0
August	0
September	0
October	0
November	0
December	0

3.4.2.5 Pressured Ice

Pressured Ice is becoming less of a concern in the Grand Banks and the Flemish Pass due to the decreasing sea ice build up noted previously, however it is still extraordinarily hazardous to marine vessels. Pressured Ice is formed when ice drifts or the sea edges of fast ice encounter each other and deformation of the surface and further compaction of the ice develop (Banda, Goerlandt, Montewka & Kujala, 2015). It is especially prominent when sea ice survives melting seasons. One of the major concerns with pressured ice, or ice build up greater than 15cm, is that it begins to develop ridges which can be hazardous even to ships built explicitly for artic sea travel and ice-breaking activities. Another specific danger of pressured pack ice is that it is difficult to identify and distinguish between less concerning sea ice drift, especially if it is old ice that has accumulated some snow. Often, pressured ice is only detected because a ship has approached it or is already stuck in the compacted ice (Mussells, Dawson & Howell, 2017).

The approach to acquiring basic event input probabilities for pressured ice is similar to methods used to determine the input probabilities for sea ice. Using ice survey data presented in Table 3-

9, it is assumed that pressured ice is possible where ice thickness exceeds 15 cm, or approximately 6/10th of an inch as reported on in the C-Core (2015) report. Again, an initial assumption must be made of a 5% failure outcome during any time sea ice concentration is encountered equal to or greater than 6E-1. The time sensitive probabilities used are documented below in Table 3-11

Table 3-11 Annual Basic Event Probability Inputs for Pressured Ice

Month	**Input Probability**
January	1.67E-03
February	1.17E-02
March	1.33E-02
April	8.33E-03
May	0
June	0
July	0
August	0
September	0
October	0
November	0
December	0

3.4.2.6 Icebergs

Atlantic Icebergs are a common concern to a marine vessel during ice flows season. Much of the data on iceberg surveys comes from aerial reviews, which serve to warn vessels of iceberg density and sizes in preparation for logistics operations. The major concern with increased iceberg density is vessel collision with an iceberg, which would result in an accident scenario causing the logistics operation to fail. Additionally, some routing and maneuvering concerns that can cause delays to the voyage or docking if iceberg density is especially high near the start and end points of the operation.

Figure 2-7 shown in Chapter 2 shows a singular day during iceberg season that can be used to average the number of icebergs on route. The dashed line boundary identifies sea ice boundary conditions. These diagrams are available for each day of the year from the U.S Coast Guard (U.S. Coast Guard Navigation Center, 2015), allowing quick identification of the iceberg quantity per season tabulated below in Table 3-12.

Table 3-12 Weekly Averages of Iceberg Count in the Flemish Pass

	Weekly Averages					
	Week 1	**Week 2**	**Week 3**	**Week 4**	**Week 5**	**Total Average**
Jan.	0.00	0.00	0.00	0.00	0.00	0.00
Feb.	0.00	0.00	0.00	0.00	N/A	0.00
March	1.00E0	3.50E0	5.75E0	1.05E1	1.38E1	6.90E0
April	1.60E1	1.35E1	1.05E1	1.00E1	1.76E1	1.35E0
May	1.73E1	2.08E1	1.92E1	1.58E1	7.50E0	1.61E0
June	5.00E0	4.63E0	6.50E0	6.50E0	1.23E1	6.99E0
July	1.01E1	6.88E0	6.13E0	6.30E-1	1.00E0	4.95E0
Aug.	3.80E-1	0	0	0	0	8.0E-2
Sept.	0	0	0	0	0	0
Oct.	0	0	0	0	0	0
Nov.	0	0	0	0	0	0
Dec.	0	0	0	0	0	0

Defining the average size of each iceberg is challenging, as identifiable recorded icebergs can range from small 15m in length to over 215m length, considered large. C-Core (2015) describes iceberg sizes of “small”, “medium”, “large”, and “very large” based on waterline length as shown in Figure 3-8.

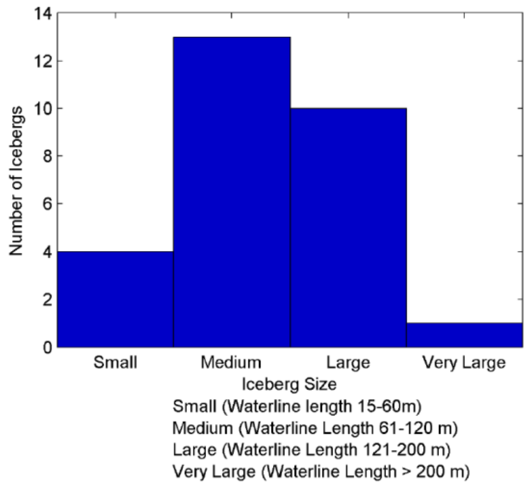

Figure 3-8 Example of Iceberg Count by Size (C-Core, 2015)

Given icebergs are commonly recorded at around 120m in length, corresponding to an overhead area of $14,400m^2$. Given this, a rough estimation of iceberg density from an overhead perspective can be obtained and this factor of iceberg density can be used when considering the probability of vessel encounter or collision. This approximation for areal iceberg density, while conservative, lines up closely with the areal density documented in the Metocean Study Final Report Vol. 2 (C-Core, 2015), as seen in Figure 3-9**.** The quality of iceberg drift models is incorporated into data uncertainty analysis techniques used in Chapter 4. In application, logistics planning quality and vessel routing will contribute to iceberg impact probability. An advantage of a network-based model that is updated based on new data and evidence is that a problem such as this would be identified through model analysis and proper mitigation efforts such as training for logistics coordinators could be put in place.

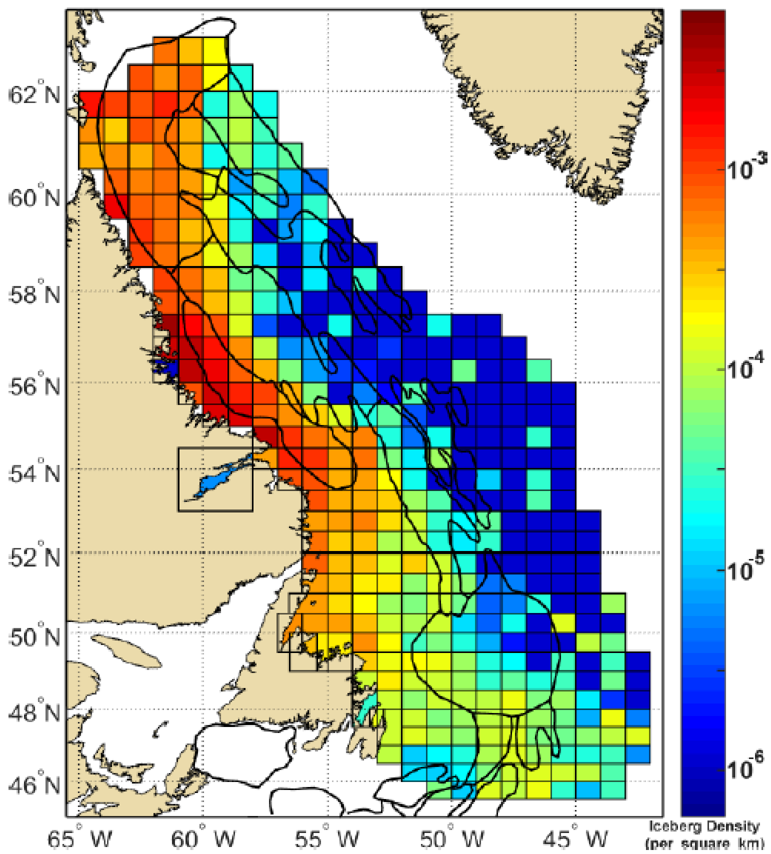

Figure 3-9 Iceberg Aerial Density (C-Core, 2015)

The basic event initial inputs are shown in Table 3-13; they are representative of the seasonal iceberg density of the Flemish Pass region and are corroborated by recent research on modelling marine logistics operations (Afenyo et al., 2017).

Table 3-13 Annual Basic Event Probability Inputs for Failure due to Iceberg Encounter

Month	Input Probability
January	0
February	0
March	1.13E-02
April	2.21E-02
May	2.63E-02
June	1.14E-02
July	8.10E-03
August	1.23E-04
September	0
October	0
November	0
December	0

3.4.2.7 Visibility

Poor environmental conditions can manifest in the form of reduced visibility during a logistics operation. Visibility concerns off the coast of Newfoundland and Labrador are associated with fog conditions. The occurrence of fog was modelled by C-Core (2015) using the approach of the National Centers for Environmental Prediction (NCEP) and the annual outcomes are presented in Figure 3-10 for extreme cases in the region where visibility is expected to be minimal.

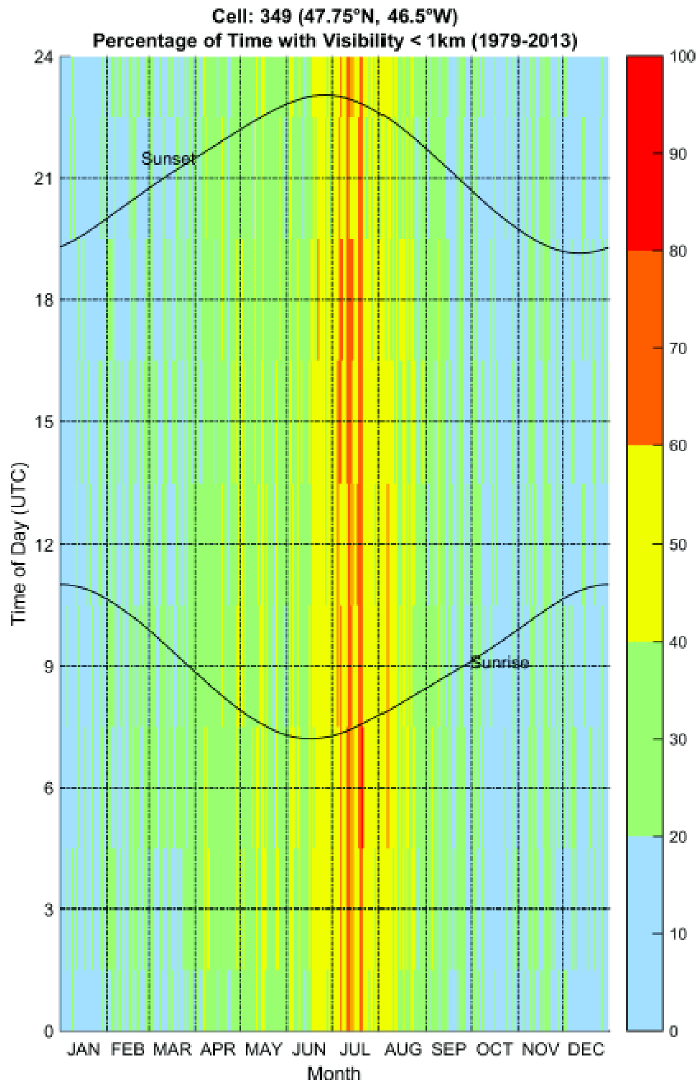

Figure 3-10 Annual Visibility Time less than 1 Kilometer in the Flemish Pass (C-Core, 2015)

The visibility thresholds presented in the C-Core (2015) report are in line with the ISO 19906:2010(E) classifications, where visibility ranges of less than one kilometer, less than two kilometers, and less than five nautical miles are considered. A visibility range of less than one kilometer is used to indicate foggy conditions that could affect a ship's response time to maneuvering around obstacles like pack ice during a voyage, or in extreme cases, affect docking and offloading procedures where precision is always required to avoid a collision.

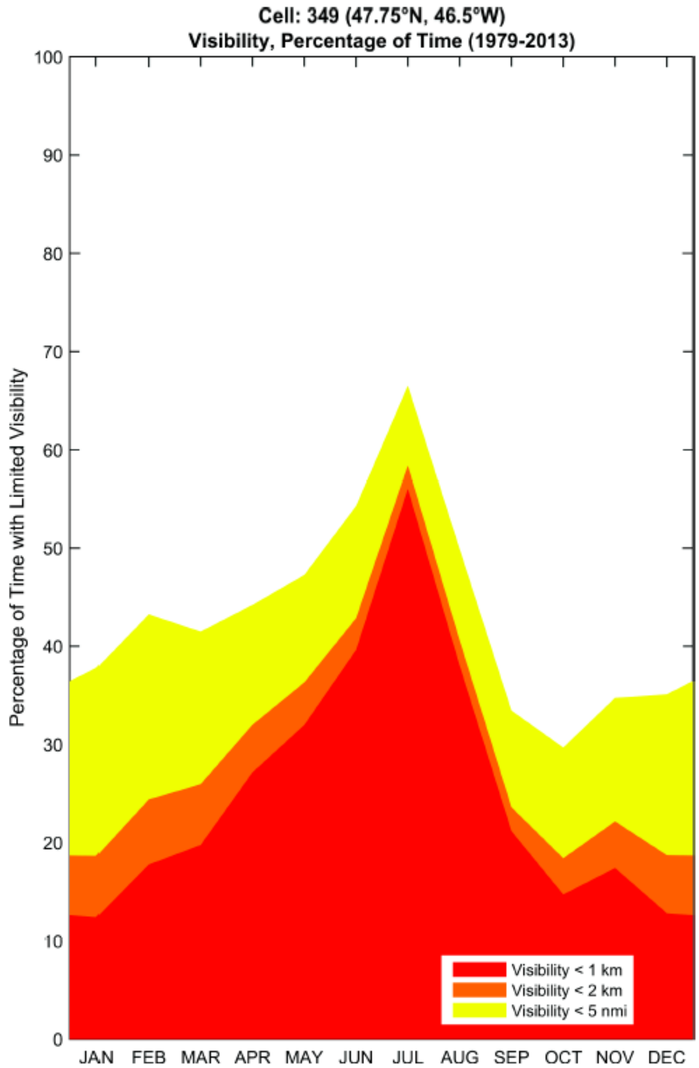

Figure 3-11 Flemish Pass Overall Annual Visibility Profile (C-Core, 2015)

A visibility annual profile is presented in Figure 3-11, where a percentage of hours with reduced visibility in a day of each of the months throughout the year is shown.

The basic event initial inputs are shown in Table 3-14; they are representative of visibility issues expected in the Flemish Pass region and are corroborated by recent research on modelling of marine logistics operations in similar regions (Afenyo et al., 2017). Binary success or failure outcomes is established through a baseline assumption that failure of the "visibility" basic event will occur 0.5 percent of the time that visibility is in ranges of less than one kilometer. These basic event monthly failure rates can be updated in the model through evidence or further refined through expert opinion and data uncertainty techniques but represents well-supported starting point for analysis.

Table 3-14 Annual basic event probability inputs for visibility concerns

Month	**Input Probability**
January	6.00E-04
February	9.00E-04
March	9.50E-04
April	1.25E-03
May	1.50E-03
June	2.00E-03
July	3.00E-03
August	1.90E-03
September	1.00E-03
October	7.50E-04
November	9.00E-04
December	6.50E-04

Chapter 4 Results and Discussion

4.1 Fault Tree Analysis

Analyzing the fault tree diagram presented in Chapter 3 requires only Boolean algebra as all basic and intermediate events are connected through OR gates. The top event "Logistics Operation Failure" probability can be calculated utilizing Eq. (2). Table 4-1 below shows a sample of the fault tree top event probability analysis for the month of January.

Table 4-1 Fault tree model analysis for January

Event	**Indicator**	**January Results**
Vessel Safety Equipment Readiness	X1.1.3	3.94E-03
Departure Readiness	X1.1	4.99E-03
Ice Conditions	X1.2.1.2, X2.1.2	3.00E-03
Environmental Conditions	X1.2.1, X2.1	2.15E-02
Communications Failure	X1.2.3.1	4.10E-04
Technical Operation Failure	X1.2.3	5.12E-04
Unobstructed Voyage	X1.2	2.24E-02
Promptness	X1	2.72E-02
Offloading and Docking	X2	2.39E-02
Logistics Operation Failure	X	5.05E-02

With time sensitive basic event probability inputs as described in Chapter 3, monthly top event probability outcomes can be determined by performing the assessment above for each month. The full range of outcomes annually is documented in Appendix A. The failure probability of the logistics operation in an average January, without incorporating data uncertainty, is 5.05E-2. The fault tree model indicates that February poses the highest risk to marine logistics operations, with the probability of failure for the operation increasing to 1.13E-1. This represents an increase in risk factor of nine times between the most hazardous month of the year in the Flemish Pass and the least hazardous, August.

4.2 Uncertainty Analysis

Triangular fuzzy sets are used in this study to account for data uncertainty of the models. Reasonable minimum and maximum expected probabilities, p_l and p_m, must first be assigned. Using Eq. (5) the minimum and maximum values at various α-cut levels can be obtained. Realistic absolute maximum and minimum error probabilities at +100% and -50% of basic event failure inputs, which are align with industry standard estimating practices for Class 5 estimates, have been selected. The calculations for basic events which are not time-sensitive are demonstrated in Table 4-2, at $\alpha = 0.9$ confidence interval.

Table 4-2 Triangular Fuzzy Event Inputs for Non-Time Sensitive Probabilities

Triangular Fuzzy Numbers, α = 0.9							
Indicator	**Event Name**	**No Error Considered**	**Minimum Value (p_l)**	**Most Likely (p_m)**	**Maximum Value (p_u)**	$p_l^{\alpha=0.9}$	$p_m^{\alpha=0.9}$
X1.1.1	Fuel Availability	3.97E-04	1.99E-04	3.97E-04	7.94E-04	3.77E-04	4.37E-04
X1.1.2	Crew Availability	3.97E-04	1.99E-04	3.97E-04	7.94E-04	3.77E-04	4.37E-04
X1.1.3.1	Lifesaving Appliances	1.00E-03	5.00E-04	1.00E-03	2.00E-03	9.50E-04	1.10E-03
X1.1.3.2	Firefighting Equipment	3.97E-04	1.99E-04	3.97E-04	7.94E-04	3.77E-04	4.37E-04
X1.1.3.3	Navigation Equipment	2.55E-03	1.28E-03	2.55E-03	5.10E-03	2.42E-03	2.81E-03
X1.1.4, X1.2.4	Engine Issues	2.60E-04	1.30E-04	2.60E-04	5.20E-04	2.47E-04	2.86E-04
X1.2.2	Hull Integrity	1.33E-04	6.65E-05	1.33E-04	2.66E-04	1.26E-04	1.46E-04
X1.2.3.1.1	Mechanical Failure (Comms.)	1.00E-05	5.00E-06	1.00E-05	2.00E-05	9.50E-06	1.10E-05
X1.2.3.1.2	Software, Controls System Failure	4.00E-04	2.00E-04	4.00E-04	8.00E-04	3.80E-04	4.40E-04
X1.2.3.2	Navigation Failure	2.00E-06	1.00E-06	2.00E-06	4.00E-06	1.90E-06	2.20E-06
X1.2.3.3	Operation System Failure	1.00E-04	5.00E-05	1.00E-04	2.00E-04	9.50E-05	1.10E-04
X2.2	Collision	2.20E-03	1.10E-03	2.20E-03	4.40E-03	2.09E-03	2.42E-03
X2.3	Grounding Failure	3.00E-05	1.50E-05	3.00E-05	6.00E-05	2.85E-05	3.30E-05
X2.4	Human Error	3.00E-04	1.50E-04	3.00E-04	6.00E-04	2.85E-04	3.30E-04

Table 4-3 Defuzzification Crisp Probability Comparisons at Various α-cut Levels

Month	**Logistics Failure Rate (No Uncertainty Considered)**	**Crisp $p^{\alpha=0.85}$**	**Percent Deviation**	**Crisp $p^{\alpha=0.90}$**	**Percent Deviation**	**Crisp $p^{\alpha=0.95}$**	**Percent Deviation**
January	5.05E-02	5.27E-02	4.08	5.20E-02	2.77	5.13E-02	1.41
February	1.13E-01	1.18E-01	3.99	1.16E-01	2.71	1.14E-01	1.38
March	1.11E-01	1.15E-01	3.99	1.14E-01	2.71	1.12E-01	1.38
April	1.00E-01	1.04E-01	4.02	1.03E-01	2.73	1.01E-01	1.39
May	6.90E-02	7.19E-02	4.09	7.10E-02	2.77	7.00E-02	1.41
June	3.48E-02	3.63E-02	4.07	3.58E-02	2.76	3.53E-02	1.40
July	3.02E-02	3.15E-02	4.05	3.11E-02	2.74	3.07E-02	1.39
August	1.24E-02	1.29E-02	3.81	1.27E-02	2.58	1.26E-02	1.31
September	1.63E-02	1.70E-02	3.91	1.68E-02	2.65	1.65E-02	1.34
October	1.78E-02	1.85E-02	3.94	1.83E-02	2.67	1.80E-02	1.35
November	2.20E-02	2.29E-02	4.00	2.26E-02	2.70	2.23E-02	1.37
December	3.55E-02	3.70E-02	4.07	3.65E-02	2.75	3.60E-02	1.40

The results for $p_l^{\alpha=0.9}$ and $p_m^{\alpha=0.9}$ are shown in Table 4-2, and in Tables B1 through to Table B12 found in Appendix B, were repeated for α = 0.95, and α = 0.85. Once these were obtained, crisp outcome probabilities were calculated for top event failure probability calculated for each α-cut level, for each month of the year. The crisp probability outcomes were obtained using the centre of area method and $p^{\alpha=0.85}$, $p^{\alpha=0.90}$, and $p^{\alpha=0.95}$ are compared in Table 4-3 above. Even with significant data uncertainty considered, such as noted with $p^{\alpha=0.85}$ crisp probabilities using fuzzy basic event inputs, the fault tree model analysis indicates significant variation in marine logistics operation failure seasonally. Figure 4-1 below graphically represents the percent deviation noted in Table 4-3 and demonstrates that the variation in logistics operation failure rate seasonally is much greater than the variation when considering data uncertainty, even at $p_l^{\alpha=0.85}$.

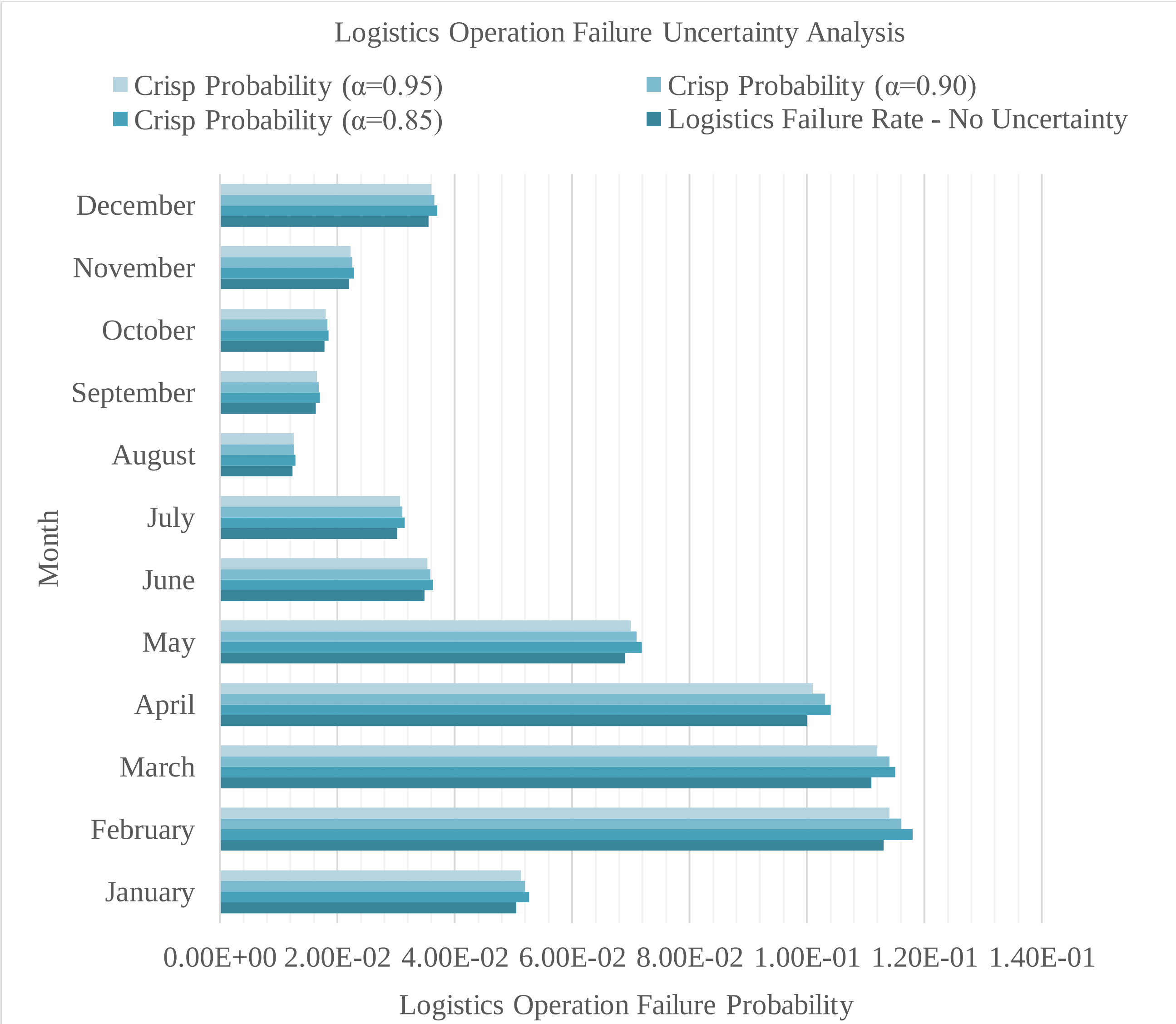

Figure 4-1 Logistics Operation Failure Uncertainty Analysis

4.3 Bayesian Network Modelling and Results

The fault tree is a useful tool for crude accident modelling, and there are methods for refining the model presented in this study further; however, model refinement and the addition of mitigation efforts are much more intuitive and comprehensive in a network-based model. Using the approach outlined by Khakzad et al. (2011), the Bayesian network can first be constructed with the same failure logic as the fault tree model. This is demonstrated in Figure 4-1 with time sensitive probability from the month of February used to demonstrate.

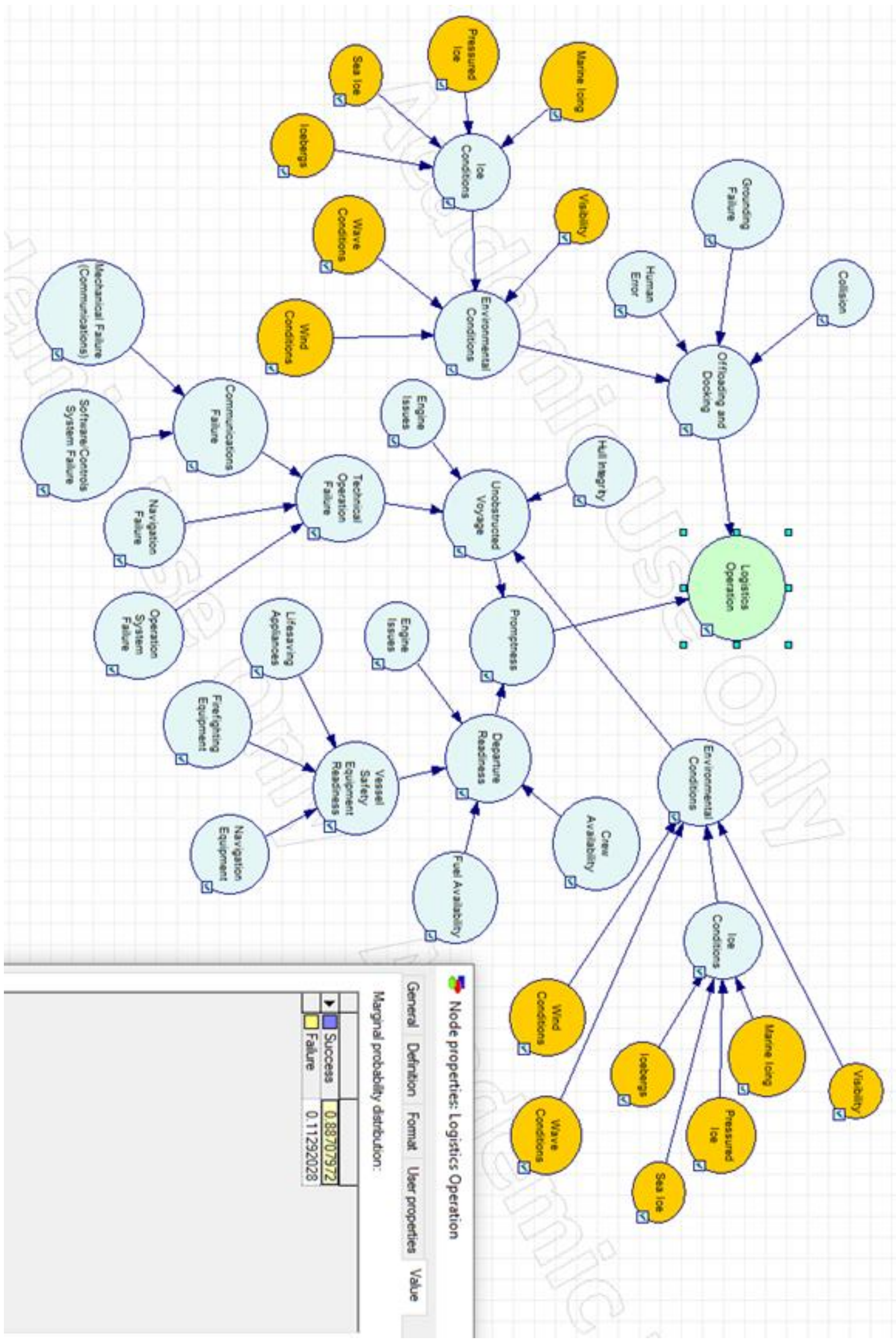

Figure 4-2 Fault Tree Network Mapped to a Bayesian Network

With no error or data uncertainty considered, Figure 4-2 aligns with the logistics operation failure probability output shown for February in Table A1, 1.13E-1, as the conditional probabilities tables input are designed to mirror the functionality of OR gates in a fault tree model.

With the fault tree mapped into a network-based model, there are changes that can be made to the Bayesian network that more accurately reflect the real-world scenario. The failures due to environmental conditions and engine failures, which have duplicated events and basic events in fault tree models and in Figure 4-2, can be considered as interdependent. This is to say that concerning predictive modelling, engine issues are not significantly more or less likely to happen either during a voyage or departure, and environmental conditions are much more highly variable monthly than they are within a 24-hour period while travelling from one destination to another in the same region. These changes are reflected in the model shown in Figure 4-3 below, again using February basic event failure probabilities for events that are time-sensitive.

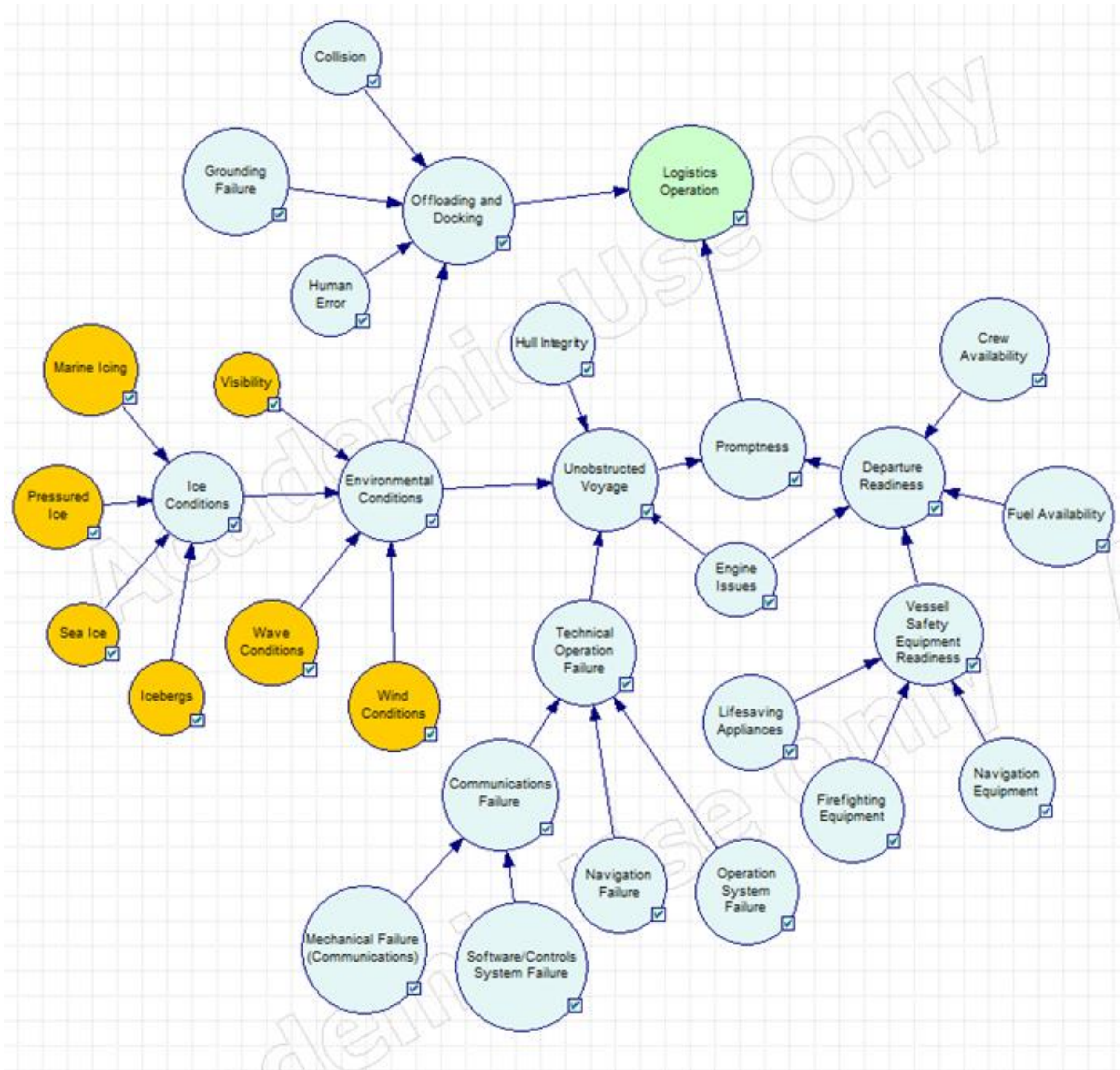

Figure 4-3 Duplication of Basic and Intermediate Events Removed from Bayesian Network

Throughout Chapter 3, relationships cited between environmental conditions would indicate that the independent failures of each condition under consideration as represented in the fault tree are not reflective of a realistic scenario. Marine icing, for example, while obviously dependent on seasonal temperatures required for freezing precipitation, is also highly dependent on wind speeds. There is also a strong causal relationship between wind speeds and wave heights recorded. Typically, wind speeds are problematic for a large marine vessel because they result in harsh sea conditions. Additionally, there is a complex relationship between sea ice or pack ice and wave conditions that would be hazardous to large vessels. While at the edge of an ice field, wave activity can break up and loosen ice formations. On a macro-scale, ocean waves propagating into an ice field are observed to decrease in amplitude, and subsequently, significant wave heights would be expected to decrease (Squire, 2018). With these noted dependencies, the environmental conditions proposed changes are illustrated in Figure 4-4.

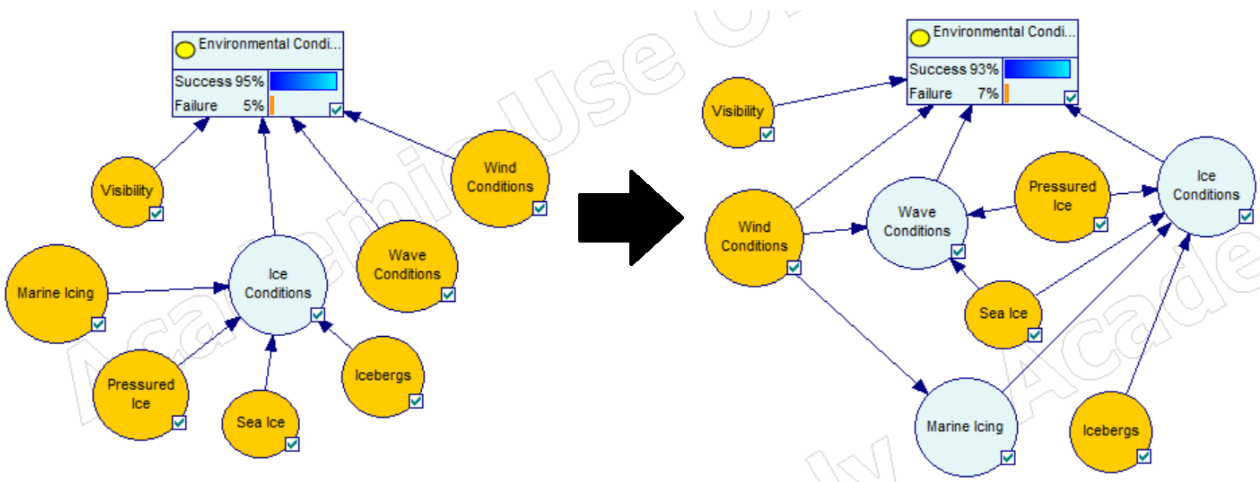

Figure 4-4 Transformation of environmental conditions intermediate event subnetwork

While it is possible to emulate the new network-based model predicting the failure rate of environmental conditions in a fault tree, Figure 4-4 demonstrates the flexibility of updating a model based on new information on dependencies between basic or intermediate events. Assumptions must be made on conditional probability tables regarding dependencies between events and are modified to reflect seasonal dependencies, “wave conditions” and “marine icing” are no longer basic events, and thus their outcome probabilities depend on the basic event inputs and their relative dependencies. The basic event inputs for February are used to refine the Bayesian Network, but the annual seasonal changes require a conditional probability review.

Table 4-4 Comparing Failure due to Wind Conditions and Marine Icing

Month	Failure Probability - Wind Conditions	Failure Probability - Marine Icing	Ratio
January	1.40E-02	6.67E-04	21.0
February	1.70E-02	1.69E-03	10.0
March	4.00E-03	1.69E-03	2.36
April	1.00E-03	3.23E-04	3.10
May	0	0	0
June	0	0	0
July	0	0	0
August	0	0	0
September	2.00E-03	0	0
October	3.00E-03	0	0
November	5.00E-03	0	0
December	1.00E-02	1.61E-04	62.0

The above Table 4-4 shows the monthly ratio of failure likelihood due to wind and marine icing in the original fault tree model. As observed, while wind conditions are a factor in the hazard levels of marine icing, if there is seasonally little icing occurring, such as in September and October, the conditional probability table will need to be updated to reflect this. Conversely, in February, March, and April, extreme winds would have a greater impact on icing failure rates. A comparison of conditional probability tables used between February and September is demonstrated below in Table 4-5 and Table 4-6. As icing is not expected to occur in September, despite the failure probability of wind conditions exceeding zero, Marine Icing will always have a success outcome in September. For the month of February, while it is true to say that failure due to high winds will not always result in failure due to marine icing, binary probability inputs are utilized regardless as wind conditions are already linked directly to environmental conditions failure, such that in the event there is a failure due to wind conditions, the intermediate node would be a resultant failure regardless.

Table 4-5 Marine Icing Conditional Probability Table in the Month of February

February		
Wind Conditions	**Success**	**Failure**
Success	9.98E-1	0
Failure	2.00E-3	1

Table 4-6 Marine Icing Conditional Probability Table in the Month of September

September		
Wind Conditions	**Success**	**Failure**
Success	1	1
Failure	0	0

Similarly, for the effects of sea ice and pressurized ice on ocean waves propagating into an ice field, it is observed from the North American Ice Service diagrams (U.S. Coast Guard), shown in Figure 4-4, that the sea ice has retreated far up to the coast of Labrador in Atlantic Canada by June. Conditional probability tables showing the dependency of wave conditions on sea ice are updated to reflect whether sea ice is expected to be present and in what capacity.

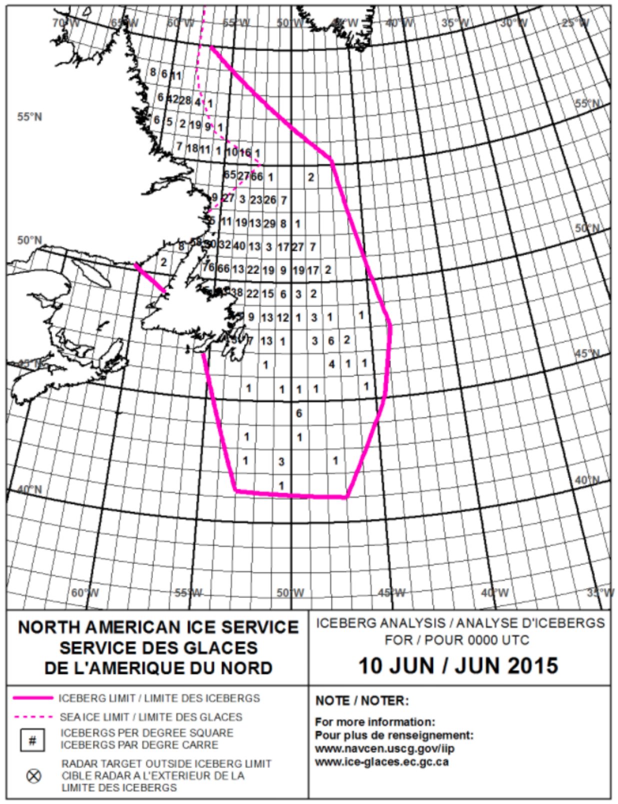

Figure 4-5 Sea Ice Conditions to Expect in June 2015 in the Atlantic Ocean

(U.S. Coast Guard, 2015)

Another concern that has been carried forward from the fault tree analysis is the impacts of human error on the accident model. The model currently only has human error considered at the docking and offloading phase of the operation; however, every phase of the operation has a human element that is relied upon for success. Thus, the human error considered in the Bayesian network should reflect that relationship. Human error could reflect that relationship through an event which affects any other event that has a human element, for example “Crew Availability”. However, if it is conditionally represented as a failure mode for each phase of the operation, it can also be appropriately considered, as all events with human elements can also fail with causes that are not derivatives of a human error. To avoid model complexity with many relationships stemming from a human error event, it is considered as a failure mode of the "promptness" intermediate event. This event includes the other two considered phases of the logistics operation. The final phase of the operation offloading and docking, also includes human error as a failure mode.

Additionally, viewing human error as a basic event that could only be variable among seasonal models would not be in line with what research shows are its causal factors. As Rothblum (2000) indicates, both the technology and apparatus being used, and the environment the user is placed in, are large drivers behind human error occurrences. For this reason, environmental conditions, now represented in Figure 4-4, will impact human error failure occurrences. The simplified final Bayesian network for logistics operation failure is then depicted in Figure 4-6.

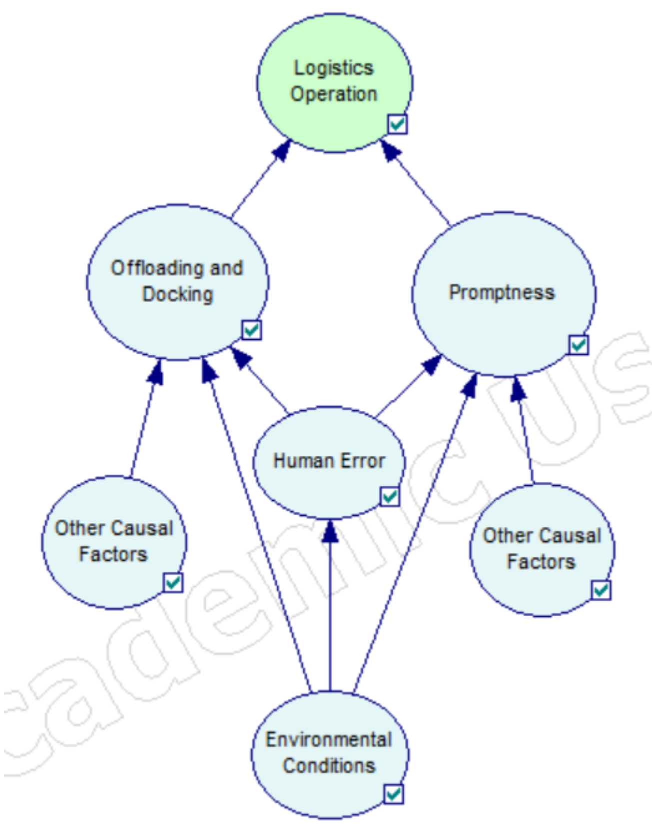

Figure 4-6 Simplified Bayesian Network Model

This change in human error representation contributes an additional accuracy element in the Bayesian network model in that environmental conditions now have an impact on all phases of the logistics operation through the increased human performance issues observed during harsh conditions.

Including the effects of leaky noisy OR-gates in the Bayesian network model is another method to improve model accuracy given the multitude of other unconsidered effects on the model that there are. The model development process identifies basic events which can contribute to the ultimate failure of a logistics operation; however, there are other external factors which may not be currently considered. These factors are omitted during the development of the model, either because they would insignificantly affect the failure probability outcomes due to their improbability of occurrence, or they could be currently unknown causal factors. For each phase of the operation, a leaky probability of failure of 1.0E-4 has been applied, which results in a conditional probability table for each corresponding intermediate event that includes a 1.0E-4 failure rate when all children events have a success result. Incorporating these conditional probability table updates and other Bayesian network model refinements discussed results in the model depicted in Figure 4-7 below.

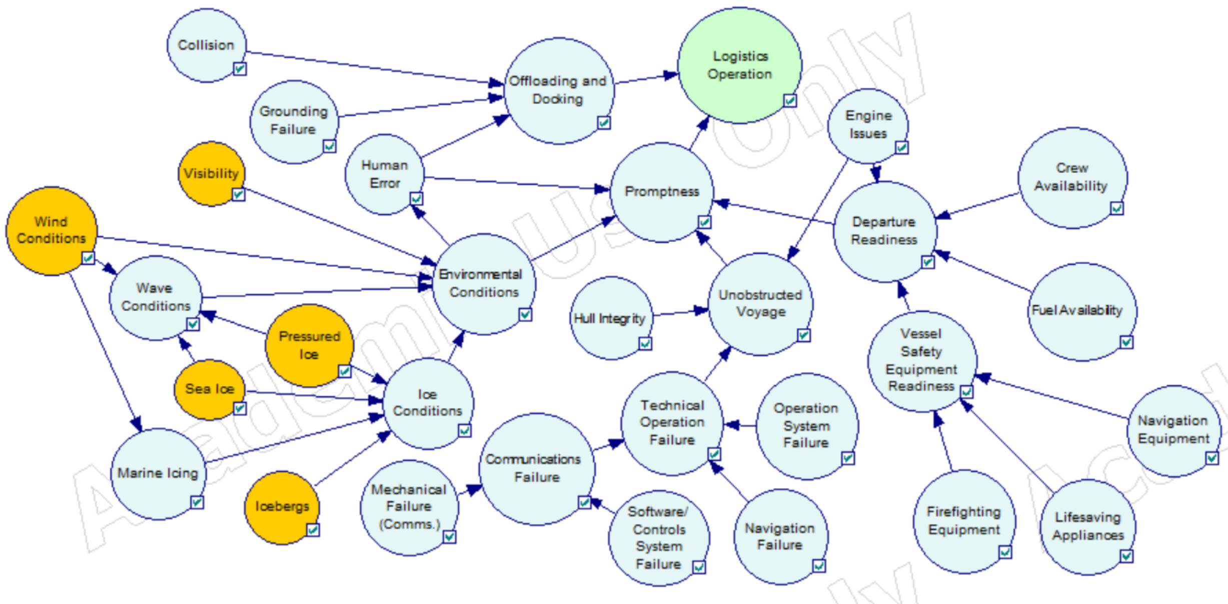

Figure 4-7 Refined Bayesian Network Model

4.4 Mitigation of Accidents

Given a reasonably accurate accident model of a marine logistics operation, accident prevention and mitigation tactics can be analyzed quantitatively. It is a fortunate circumstance that employee safety is the overriding priority during all operations in the oil and gas industry today, logistics or otherwise, but there are always economic and budgetary constraints. It is within a company's best interest to minimize safety incidents, injuries, and casualties, for both ethical and budgetary reasons. Modern industry accidents are extremely expensive; as early as 1978, it was proposed an expenditure of the equivalent of $34 million Canadian dollars over a period of ten years would appear to be cost effective if its primary purpose were to avert accidents involving large vessels (Fujii, 1978). Adjusting for inflation, this is $142.8 million Canadian dollars over a ten-year period.

This leaves the question of how to properly allocate a budget for accident prevention and mitigating strategies to minimize operation failure rates. Rahman et al. (2020) proposes a method of calculating risk reduction as a percentage of the overall reduction in logistics operation failure rate. Priority of this risk reduction percentage can be established through analysis of the resultant risk reduction percentage per dollar of expenditure. With a model that is sensitive to seasonal changes, the focus of accident prevention can be further narrowed to maximizing risk mitigation while considering efficiency, from a monetary perspective, of strategies throughout the year. The first step is to identify critical factors in the refined Bayesian network. The posterior probabilities given evidence of failure set on the logistics operation node indicates what factors are of priority. Figure 4-8 and Figure 4-9 show posterior probabilities in February and August.

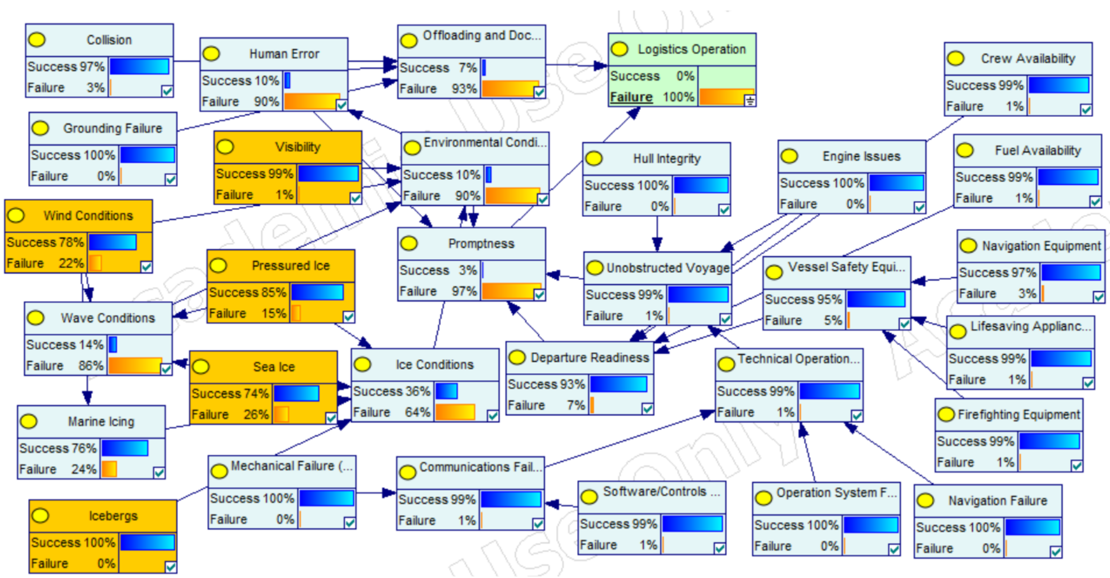

Figure 4-8 Posterior Probabilities of Refined Bayesian Network in February

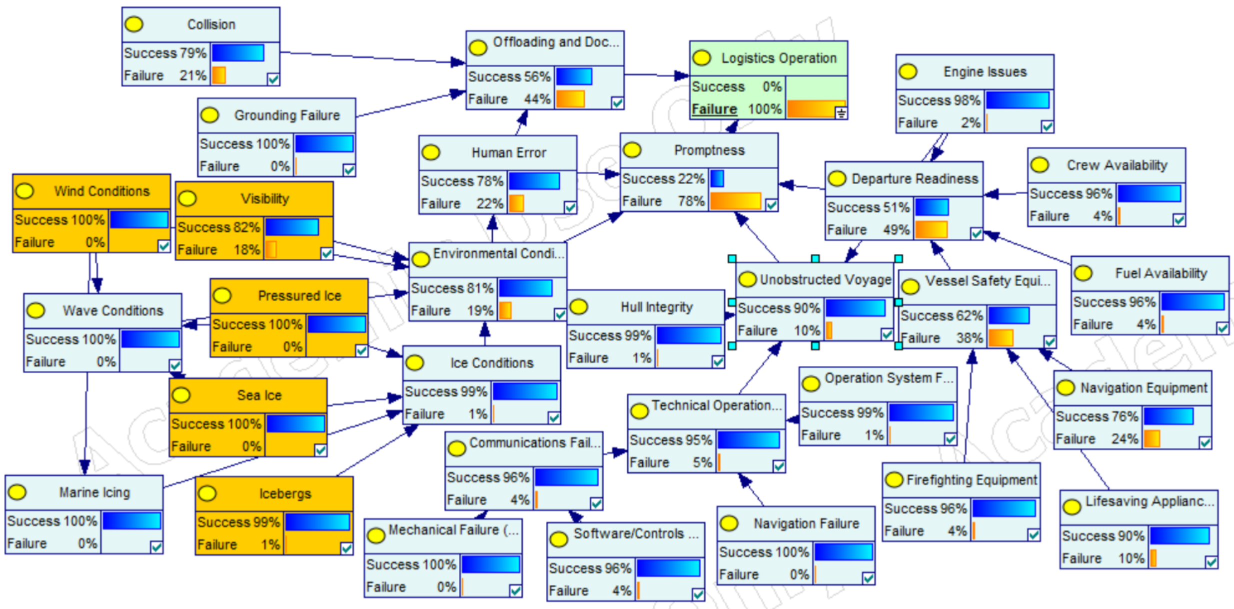

Figure 4-9 Posterior Probabilities of Refined Bayesian Network in August

Figure 4-8 and Figure 4-9 graphically represent the problem of accident prevention considering time sensitive probabilities. Posterior probabilities given evidence of logistics operation failure shift significantly; environmental conditions such as wind speed, wave height, and ice conditions become marginally significant, and accident prevention would be more effective utilizing tactics reducing the failure events associated with readiness and protection of vessel equipment. The posterior probabilities reflected in Figures 4-8 and 4-9 are shown numerically in Appendix C for all months of the year. The posterior probabilities calculated from setting evidence of logistics operation failure in each month can be analyzed in two ways to balance prioritization of accident prevention methods, depicted in Table 4-7. This first method is a review of the average posterior probability annually of each event. Human error, although an intermediate node in the Bayesian network now through model refinement, has been included in this analysis. The second method is to review the criticality index of each event, which is the ratio of the annual average posterior probability and prior probability. This index indicates which of the events will more efficiently change the average failure rate annually, in the event the failure probability can be lowered using some mitigation technique. For the events that are not time-sensitive or have time-sensitive child nodes, their critical index is equivalent.

Table 4-7 Analysis of Risk Mitigation Priorities

Event	**Average Prior Failure Probability**	**Average Posterior Failure Probability**	**Critical Index**
Collision	2.20E-03	8.09E-02	36.8
Grounding Failure	3.00E-05	1.10E-03	36.8
Engine Issues	2.60E-04	9.57E-03	36.8
Crew Availability	3.97E-04	1.46E-02	36.8
Fuel Availability	3.97E-04	1.46E-02	36.8
Navigation Equipment	2.55E-03	9.38E-02	36.8
Lifesaving Appliances	1.00E-03	3.68E-02	36.8
Firefighting Equipment	3.97E-04	1.46E-02	36.8
Operation System Failure	1.00E-04	3.68E-03	36.8
Navigation Failure	2.00E-06	7.36E-05	36.8
Software/Controls System Failure	4.00E-04	1.47E-02	36.8
Mechanical Failure (Communications)	1.00E-05	3.68E-04	36.8
Hull Integrity	1.33E-04	4.89E-03	36.8
Visibility	1.28E-03	5.47E-02	42.6
Wind Conditions	4.67E-03	1.10E-01	23.6
Sea Ice	5.06E-03	6.73E-02	13.3
Icebergs	6.62E-03	1.70E-01	25.7
Pressured Ice	2.92E-03	3.77E-02	12.9
Human Error	3.09E-02	7.06E-01	22.8

Human error throughout the year is a contributing factor 70.6% of the time there is evidence of a logistics operation failure. This finding supports the importance of human performance training as an area of risk mitigation focus across most industries, including marine transportation. From the results presented in Appendix C, it is evident that environmental conditions are a leading cause of logistics operations failures, though as shown in Table 4-7, except for visibility, have low critical indices annually. What this means from a practical perspective is that while mitigation efforts are important to ensure high success rates of logistics operation, capital expenditures may be more effective in other risk mitigation areas. For example, mitigation strategies for environmental effects such as specialized ice breaking ships being garnered through a contracted solution to minimize expenditures year-round. Those funds can be more efficiently used to reduce the annual operation failure rate. Further mitigation strategies such as buffer inventory availability, which would allow for more flexible logistics planning and scheduling when combined with state-of-the-art weather prediction strategies, can also be justified in upfront planning of an operation in the Flemish pass, where capital expenditures to reduce risk can be minimized prior to construction and remain effective over the life of the operation. Analyzing both the posterior probabilities and the criticality indices, the decision point outlined in Figure 4-10 below can be completed, and the risk reduction calculation can be completed.

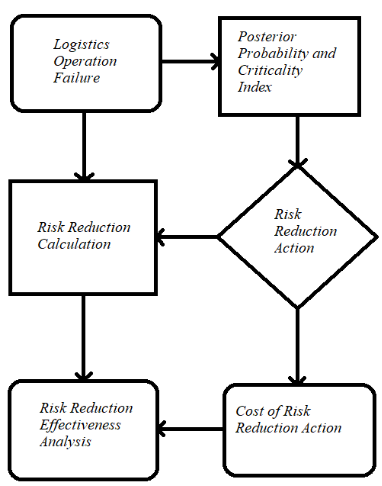

Figure 4-10 Decision Tree for Risk Reduction Effectiveness Analysis

To demonstrate this process, two hypothetical risk mitigation strategies are proposed, with the goal being to simulate an option selection scenario based on realistic budget constraints and safety concerns. Consider a scenario where the option of purchasing and crewing a specialized ice breaking vessel is being weighed against a third-party contracted solution. The subsequent example mitigation node is depicted in purple in Figure 4-11, in the network for the month of March.

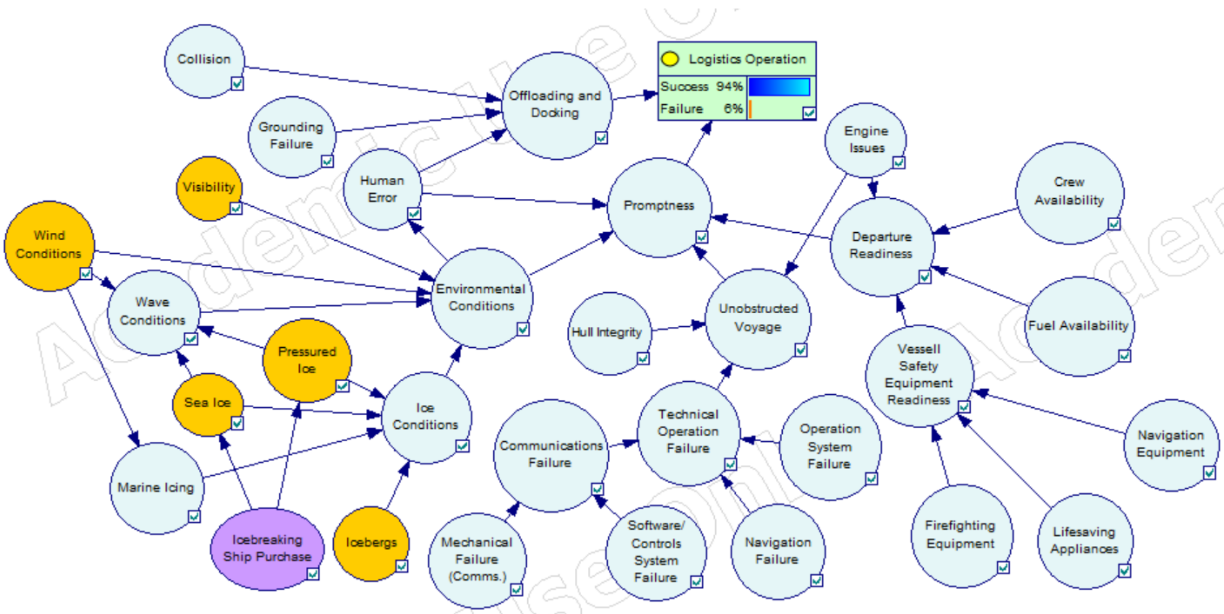

Figure 4-11 Bayesian Network Model with Icebreaking Ship Purchase Mitigation

Rahman et al. (2020) presents a similar example with training being used to mitigate human performance errors. The subsequent impacts on the new probability of the failure of "Sea Ice" and "Pressured Ice" can be calculated similarly utilizing the law of total probability with Eq. (9), where $P(SI|IB_{SI})$ refers to the conditional probability of sea ice failure given that icebreaking mitigation has failed, and $P(IB_{SI})$ is the failure probability of the icebreaking activity.

$$P(SI) = P(SI|IB_{SI})\ X\ P(IB_{SI}) + P\left(SI\middle|\overline{IB}_{SI}\right) X\ P(\overline{IB}_{SI}) \quad (9)$$

Given the conditional probability table presented in Table 4-8, and assuming that the failure rate of icebreaking activities is 0.01, the probability of failure of the sea ice node can be recalculated as $P(SI)$ = (2.17E-2 X 0.01) + (2.17E-3 X 0.99) = 2.37E-3.

Table 4-8 New Conditional Probability Table for Sea Ice in March

	Icebreaking Ship Purchase	
Sea Ice	Success	Failure
Success	9.97E-1	9.78E-1
Failure	2.17E-3	2.17E-2

A similar process is modelled for the mitigating effects of purchasing a specialized icebreaking vessel on pressured ice as shown in Figure 4-11, and a new logistics operation failure rate is calculated. For the month of March, the expected logistics operation failure rate is reduced from 8.72E-2 to 5.80E-2, representing a risk reduction of 33.5 percent. This process is repeated for each of the twelve months of the year, and then the new average logistics failure rate is shown in Table 4-9. If the third-party ice breaking service has a higher failure probability of 3.0E-1, due to scheduling difficulties and competing clients, the reduction in logistic operation failure expected from the two options can be compared and analyzed quantitatively based on their cost.

Table 4-9 Risk Mitigation Options Analysis

Scenario	**Average Unmitigated Logistics Operation Failure Rate**	**Average Mitigated Logistics Operation Failure Rate**	**Risk Reduction (%)**	**Estimated Annual Expenditure ($M)**	**Percent of Risk Reduction per $1M**
Icebreaking Ship Purchase	3.97E-2	3.31E-2	16.70%	22	0.759%
Third Party Service	397E-2	3.50E-2	11.74%	3	3.91%

Considering the annual risk reduction and seasonal changes is important; while the risk reduction in March is 33.5 percent, the purchasing solution involves large capital expenditures annualized to spread cost to the months where sea ice and pressurized ice are of marginal or no concern. This reduced the attractiveness of this option in this case.

4.5 Model Comparisons

This study indicates that annually, the failure probability of a marine logistics operation servicing the Flemish Pass area has significant variation. In recent research, Rahman et al. (2019) demonstrated that the expected failure probability of an emergency marine logistics operation using a fault tree model was between 7.78E-2 and 7.68E-2, varying based on the level of data uncertainty considered. The average probability of failure with uncertainty considered across the twelve months of the year found in the fault tree analysis presented here is a comparable 5.25E-2, but the failure probability in February is 221% higher than the annual average in the fault tree model.

Modelling the marine logistics operation as a Bayesian Network further supports this observed seasonal variation as demonstrated in Table 4-10 below. It is noteworthy that the failure rate ratio between the failure rate in August and February, the most and least accident-prone months according to the fault tree model, is similar. While this indicates consistency in the findings of seasonal changes in logistics operation risk assessment, variations such as the increased relative risk in March, September, October, and November shown in the Bayesian network results are found as well. This can be explained by the refinement of the environmental conditions and human error subnetworks and its effect on the failure results. More accurate modeling of the complex relationships between wind, waves, and other environmental effects makes the failure probability of the operation more sensitive to wind and wave conditions seasonally, in addition to extreme sea and pressured ice effects that are present in March.

Table 4-10 Final Results – Comparison between Bayesian Network and Fault Tree

	Logistics Operation Failure Rate		**Ratio of Failure Probability to February**	
Month	**Bayesian Network (No Mitigation)**	**Fault Tree $p^{\alpha=0.90}$**	**Bayesian Network (No Mitigation)**	**Fault Tree $p^{\alpha=0.90}$**
January	4.53E-02	5.20 E-02	0.59	0.45
February	7.72 E-02	1.16 E-01	1.00	1.00
March	8.72 E-02	1.14 E-01	1.13	0.98
April	7.45 E-02	1.03 E-01	0.97	0.89
May	3.91 E-02	7.10 E-02	0.51	0.61
June	2.17 E-02	3.58 E-02	0.28	0.31
July	1.94 E-02	3.11 E-02	0.25	0.27
August	1.05 E-02	1.27 E-02	0.14	0.11
September	2.13 E-02	1.68 E-02	0.28	0.14
October	2.20 E-02	1.83 E-02	0.28	0.16
November	2.41 E-02	2.26 E-02	0.31	0.19
December	3.38 E-02	3.65 E-02	0.44	0.31

Chapter 5 Conclusions and Recommendations

This thesis presents a comparison of fault tree and Bayesian network modelling techniques, and proposes a risk model to analyze marine logistics operations while considering seasonal changes in an area with harsh environmental conditions. Bayesian network refinement is completed to address interdependencies and conditional dependencies of events, and the result is a prediction and prevention analysis tool that can be used to ensure efficient and effective spending to reduce logistics operation failure rates. The main contributions of this thesis are summarized as follows:

- The identification of time sensitive prior probability inputs and their effect on baseline accuracy of a marine logistics operation model. Comprehensive analysis of the increased harshness index in the Flemish Pass in comparison with production facilities in operation outlining the relative risk increase expected.
- The direct comparison of a fault tree model and Bayesian network outcomes showing flexibility to model interdependency of events with data uncertainty considerations.
- Development of an Advanced Bayesian network, with seasonal environmental condition considered
- Consideration of historical data to enhance model accuracy and further develop applications of the model.
- Evaluation of accident prevention and mitigation strategies utilizing posterior probabilities and a criticality index, resulting in optimized capital spending to reduce logistic operation failure rates annually.
- This thesis considers time-sensitive probabilities, in addition to an in-depth analysis of environmental conditions in the specific area. In this research it is concluded that while the model is built to analyze operational challenges of marine logistics in such a way that

relevant risk management strategies can be proposed, time sensitive inputs would provide a more robust estimation.

The emergency response logistics operation failure rate produced through this model, without mitigation strategies considered, is 8.49E-02. This is comparable to the logistics operation failure rates of 7.72E-02, 8.72E-02 and 7.45E-02 found in February, March, and April, respectively, however it is more than double the annual average of 3.97E-04. What this indicates is that the Bayesian network modelling techniques used are producing repeatable results; but variation between refined networks is much less impactful than consideration of seasonal inputs.

In comparison with other research, Kum & Sahin (2015) studied marine accident causes from 1993 to 2011 based on sixty-five reported incidents, and using a fuzzy input fault tree approach, concluded that crew training, as well as more Arctic navigation training centers, would significantly reduce the frequency of accidents, specifically collision and grounding accidents. Using a similar modelling technique, Rahman et al. (2019), outline the significance of electronic/mechanical failures, in addition to human error. While data acquisition and inputs are certainly a cause for much of the variation in critical factors identified in previous research, given the results of this study, the consideration of annual risk, versus immediate or case-specific risk, would significantly alter what basic and intermediate events are influencing the top-level event failures. In the case of Arctic shipping operations, the ice hazards outlined in this thesis are persistent and at one level or another, annually, whereas in studying logistics operations off the coast of Newfoundland and Labrador, there is significant seasonal variation and risk level.

Afenyo et al., (2017) used a network-based approach to model Arctic shipping accidents. They highlighted identification of critical factors and interdependencies of basic events commonly considered in marine logistics accident modelling. The conclusion, however does cite their present methodologies rely heavily upon the inputs from literature for the probabilities. Rahman et al. (2020) use a Bayesian network approach to more accurately model a marine logistics scenario and refine the fault tree model discussed above. Expert opinion and evidence theory is relied upon to narrow uncertainty in basic event probabilities. Rahman et al. (2020) present a network that considers threats due to poor visibility, marine icing, wind, wave, sea ice, pressured ice, and icebergs as constants; this is representative of an analysis in a month such as February or March.

Both the fault tree accident model and the Bayesian network support the importance to consider the time sensitive nature of causal events. Given the significant variation in failure rates expected annually, it would be prudent to analyze accident prevention barriers and techniques considering seasonal conditions. Furthermore, acquired data indicates that many environmental conditions are changing due to global climate change, or that 100-year extremes that can be predicted, are not well represented when utilizing recent data. These findings only further support ensuring that changing environmental conditions are considered when modelling marine logistics operations, that data is reviewed periodically to ensure it is reflective of recent findings and that data uncertainty is considered.

There are limitations of this thesis that have been identified below. Continuation of marine logistics analysis should consider the time-sensitive nature of environmental conditions, and future works could expand on the effects of time-sensitivity of the model in the following ways:

- This study is reliant on assumptions relating to the frequency of environmental condition severity with accident outcome. As such, the next recommended step relevant to this research is to expand the event outcomes to be non-binary. Though interdependencies become much more complex, more outcomes such as “mild, moderate, intense, extreme” for each of the basic events pertaining to environmental conditions would lead to greater model accuracy, and more precise analysis of mitigation strategies, given the huge variation in impacts often considered in linear accident modelling.

- Analysis as to what conditions were at the time of incident, similar to how the sixty-five Arctic shipping incidents were analyzed by Kum & Sahin (2015), could then allow for updating of the assumptions regarding the actual severity of environmental conditions, which are well understood, and how they translate to incidents and accidents.
- Environmental conditions model could be improved by creating a distribution of time-sensitive inputs, as marine voyages pass through portions of the ocean that have a higher or lower overall harshness indices. This would add model complexity as environmental condition intermediate event could not be refined to a single node and subsequent subnetwork, as the weather and ocean conditions would have varying effects on the departure readiness, voyage, and offloading and docking of a given operation, depending on the location of departure, route, and destination.

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Appendix A – Fault Tree Model Results

Table A1 Fault Tree Analysis – Calculation of Event Failure Probability for each Month

Event	Indicator	January	February	March	April	May	June	July	August	September	October	November	December
Vessel Safety Equipment Readiness	X1.1.3	3.94E-03	3.94E-03	3.94E-03	3.94E-03	3.94E-03	3.94E-03	3.94E-03	3.94E-03	3.94E-03	3.94E-03	3.94E-03	3.94E-03
Departure Readiness	X1.1	4.99E-03	4.99E-03	4.99E-03	4.99E-03	4.99E-03	4.99E-03	4.99E-03	4.99E-03	4.99E-03	4.99E-03	4.99E-03	4.99E-03
Ice Conditions	X1.2.1.2, X2.1.2	3.00E-03	3.31E-02	4.72E-02	4.51E-02	2.96E-02	1.14E-02	8.10E-03	1.23E-04	0.00E+00	0.00E+00	0.00E+00	1.61E-04
Environmental Conditions	X1.2.1, X2.1	2.15E-02	5.42E-02	5.29E-02	4.73E-02	3.10E-02	1.34E-02	1.11E-02	2.02E-03	4.00E-03	4.74E-03	6.89E-03	1.38E-02
Communications Failure	X1.2.3.1	4.10E-04	4.10E-04	4.10E-04	4.10E-04	4.10E-04	4.10E-04	4.10E-04	4.10E-04	4.10E-04	4.10E-04	4.10E-04	4.10E-04
Technical Operation Failure	X1.2.3	5.12E-04	5.12E-04	5.12E-04	5.12E-04	5.12E-04	5.12E-04	5.12E-04	5.12E-04	5.12E-04	5.12E-04	5.12E-04	5.12E-04
Unobstructed Voyage	X1.2	2.24E-02	5.50E-02	5.37E-02	4.81E-02	3.19E-02	1.43E-02	1.20E-02	2.93E-03	4.90E-03	5.64E-03	7.79E-03	1.47E-02
Promptness	X1	2.72E-02	5.97E-02	5.85E-02	5.29E-02	3.67E-02	1.92E-02	1.69E-02	7.90E-03	9.86E-03	1.06E-02	1.27E-02	1.96E-02
Offloading and Docking	X2	2.39E-02	5.66E-02	5.53E-02	4.97E-02	3.35E-02	1.59E-02	1.36E-02	4.55E-03	6.51E-03	7.26E-03	9.40E-03	1.63E-02
Logistics Operation Failure	X	5.05E-02	1.13E-01	1.11E-01	1.00E-01	6.90E-02	3.48E-02	3.02E-02	1.24E-02	1.63E-02	1.78E-02	2.20E-02	3.55E-02

Appendix B – Time Sensitive Basic Event Triangular Fuzzy Sets

Table B1 January Fuzzy Basic Event Probabilities at Various α- cut Levels

					January						
Indicator	**Event Name**	**Basic Event Initial**	**Minimum Value**	**Most Likely**	**Max Value**	$p_l^{\alpha=0.9}$	$p_m^{\alpha=0.9}$	$p_l^{\alpha=0.85}$	$p_m^{\alpha=0.85}$	$p_l^{\alpha=0.95}$	$p_m^{\alpha=0.95}$
X1.2.1.1, X2.1.1	Wind Conditions	1.40E-02	8.40E-03	1.40E-02	2.80E-02	1.34E-02	1.54E-02	1.32E-02	1.61E-02	1.37E-02	1.47E-02
X1.2.1.2.1, X2.1.2.2	Marine Icing	6.67E-04	4.00E-04	6.67E-04	1.33E-03	6.40E-04	7.33E-04	6.27E-04	7.67E-04	6.53E-04	7.00E-04
X1.2.1.2.2, X2.1.2.3	Sea Ice	6.67E-04	4.00E-04	6.67E-04	1.33E-03	6.40E-04	7.33E-04	6.27E-04	7.67E-04	6.53E-04	7.00E-04
X1.2.1.2.3, X2.1.2.3	Icebergs	0	0	0	0	0	0	0	0	0	0
X1.2.1.2.4, X2.1.2.4	Pressured Ice	1.67E-03	1.00E-03	1.67E-03	3.33E-03	1.60E-03	1.83E-03	1.57E-03	1.92E-03	1.63E-03	1.75E-03
X1.2.1.3, X2.1.3	Wave Conditions	4.00E-03	2.40E-03	4.00E-03	8.00E-03	3.84E-03	4.40E-03	3.76E-03	4.60E-03	3.92E-03	4.20E-03
X1.2.1.4, X2.1.4	Visibility	6.00E-04	3.60E-04	6.00E-04	1.20E-03	5.76E-04	6.60E-04	5.64E-04	6.90E-04	5.88E-04	6.30E-04

Table B2 February Fuzzy Basic Event Probabilities at Various α- cut Levels

				February							
Indicator	**Event Name**	**Basic Event Initial**	**Minimum Value**	**Most Likely**	**Max Value**	$p_l^{\alpha=0.9}$	$p_m^{\alpha=0.9}$	$p_l^{\alpha=0.85}$	$p_m^{\alpha=0.85}$	$p_l^{\alpha=0.95}$	$p_m^{\alpha=0.95}$
X1.2.1.1, X2.1.1	Wind Conditions	1.70E-02	1.02E-02	1.70E-02	3.40E-02	1.63E-02	1.87E-02	1.60E-02	1.96E-02	1.67E-02	1.79E-02
X1.2.1.2.1, X2.1.2.2	Marine Icing	1.69E-03	1.02E-03	1.69E-03	3.39E-03	1.63E-03	1.86E-03	1.59E-03	1.95E-03	1.66E-03	1.78E-03
X1.2.1.2.2, X2.1.2.3	Sea Ice	2.00E-02	1.20E-02	2.00E-02	4.00E-02	1.92E-02	2.20E-02	1.88E-02	2.30E-02	1.96E-02	2.10E-02
X1.2.1.2.3, X2.1.2.3	Icebergs	0	0	0	0	0	0	0	0	0	0
X1.2.1.2.4, X2.1.2.4	Pressured Ice	1.17E-02	7.00E-03	1.17E-02	2.33E-02	1.12E-02	1.28E-02	1.10E-02	1.34E-02	1.14E-02	1.23E-02
X1.2.1.3, X2.1.3	Wave Conditions	4.00E-03	2.40E-03	4.00E-03	8.00E-03	3.84E-03	4.40E-03	3.76E-03	4.60E-03	3.92E-03	4.20E-03
X1.2.1.4, X2.1.4	Visibility	9.00E-04	5.40E-04	9.00E-04	1.80E-03	8.64E-04	9.90E-04	8.46E-04	1.04E-03	8.82E-04	9.45E-04

Table B3 March Fuzzy Basic Event Probabilities at Various α- cut Levels

				March							
Indicator	**Event Name**	**Basic Event Initial**	**Minimum Value**	**Most Likely**	**Max Value**	$p_l^{\alpha=0.9}$	$p_m^{\alpha=0.9}$	$p_l^{\alpha=0.85}$	$p_m^{\alpha=0.85}$	$p_l^{\alpha=0.95}$	$p_m^{\alpha=0.95}$
X1.2.1.1, X2.1.1	Wind Conditions	4.00E-03	2.40E-03	4.00E-03	8.00E-03	3.84E-03	4.40E-03	3.76E-03	4.60E-03	3.92E-03	4.20E-03
X1.2.1.2.1, X2.1.2.2	Marine Icing	1.69E-03	1.02E-03	1.69E-03	3.39E-03	1.63E-03	1.86E-03	1.59E-03	1.95E-03	1.66E-03	1.78E-03
X1.2.1.2.2, X2.1.2.3	Sea Ice	2.17E-02	1.30E-02	2.17E-02	4.33E-02	2.08E-02	2.38E-02	2.04E-02	2.49E-02	2.12E-02	2.28E-02
X1.2.1.2.3, X2.1.2.3	Icebergs	1.13E-02	6.77E-03	1.13E-02	2.26E-02	1.08E-02	1.24E-02	1.06E-02	1.30E-02	1.11E-02	1.19E-02
X1.2.1.2.4, X2.1.2.4	Pressured Ice	1.33E-02	8.00E-03	1.33E-02	2.67E-02	1.28E-02	1.47E-02	1.25E-02	1.53E-02	1.31E-02	1.40E-02
X1.2.1.3, X2.1.3	Wave Conditions	1.00E-03	6.00E-04	1.00E-03	2.00E-03	9.60E-04	1.10E-03	9.40E-04	1.15E-03	9.80E-04	1.05E-03
X1.2.1.4, X2.1.4	Visibility	9.50E-04	5.70E-04	9.50E-04	1.90E-03	9.12E-04	1.05E-03	8.93E-04	1.09E-03	9.31E-04	9.98E-04

Table B4 April Fuzzy Basic Event Probabilities at Various α- cut Levels

April											
Indicator	**Event Name**	**Basic Event Initial**	**Minimum Value**	**Most Likely**	**Max Value**	$p_l^{\alpha=0.9}$	$p_m^{\alpha=0.9}$	$p_l^{\alpha=0.85}$	$p_m^{\alpha=0.85}$	$p_l^{\alpha=0.95}$	$p_m^{\alpha=0.95}$
X1.2.1.1, X2.1.1	Wind Conditions	1.00E-03	6.00E-04	1.00E-03	2.00E-03	9.60E-04	1.10E-03	9.40E-04	1.15E-03	9.80E-04	1.05E-03
X1.2.1.2.1, X2.1.2.2	Marine Icing	3.23E-04	1.94E-04	3.23E-04	6.45E-04	3.10E-04	3.55E-04	3.03E-04	3.71E-04	3.16E-04	3.39E-04
X1.2.1.2.2, X2.1.2.3	Sea Ice	1.50E-02	9.00E-03	1.50E-02	3.00E-02	1.44E-02	1.65E-02	1.41E-02	1.73E-02	1.47E-02	1.58E-02
X1.2.1.2.3, X2.1.2.3	Icebergs	2.21E-02	1.33E-02	2.21E-02	4.43E-02	2.12E-02	2.43E-02	2.08E-02	2.55E-02	2.17E-02	2.32E-02
X1.2.1.2.4, X2.1.2.4	Pressured Ice	8.33E-03	5.00E-03	8.33E-03	1.67E-02	8.00E-03	9.17E-03	7.83E-03	9.58E-03	8.17E-03	8.75E-03
X1.2.1.3, X2.1.3	Wave Conditions	0	0	0	0	0	0	0	0	0	0
X1.2.1.4, X2.1.4	Visibility	1.25E-03	7.50E-04	1.25E-03	2.50E-03	1.20E-03	1.38E-03	1.18E-03	1.44E-03	1.23E-03	1.31E-03

Table B5 May Fuzzy Basic Event Probabilities at Various α- cut Levels

					May						
Indicator	**Event Name**	**Basic Event Initial**	**Minimum Value**	**Most Likely**	**Max Value**	$p_l^{\alpha=0.9}$	$p_m^{\alpha=0.9}$	$p_l^{\alpha=0.85}$	$p_m^{\alpha=0.85}$	$p_l^{\alpha=0.95}$	$p_m^{\alpha=0.95}$
X1.2.1.1, X2.1.1	Wind Conditions	0	0	0	0	0	0	0	0	0	0
X1.2.1.2.1, X2.1.2.2	Marine Icing	0	0	0	0	0	0	0	0	0	0
X1.2.1.2.2, X2.1.2.3	Sea Ice	3.33E-03	2.00E-03	3.33E-03	6.67E-03	3.20E-03	3.67E-03	3.13E-03	3.83E-03	3.27E-03	3.50E-03
X1.2.1.2.3, X2.1.2.3	Icebergs	2.63E-02	1.58E-02	2.63E-02	5.27E-02	2.53E-02	2.90E-02	2.47E-02	3.03E-02	2.58E-02	2.76E-02
X1.2.1.2.4, X2.1.2.4	Pressured Ice	0	0	0	0	0	0	0	0	0	0
X1.2.1.3, X2.1.3	Wave Conditions	0	0	0	0	0	0	0	0	0	0
X1.2.1.4, X2.1.4	Visibility	1.50E-03	9.00E-04	1.50E-03	3.00E-03	1.44E-03	1.65E-03	1.41E-03	1.73E-03	1.47E-03	1.58E-03

Table B6 June Fuzzy Basic Event Probabilities at Various α- cut Levels

					June						
Indicator	**Event Name**	**Basic Event Initial**	**Minimum Value**	**Most Likely**	**Max Value**	$p_l^{\alpha=0.9}$	$p_m^{\alpha=0.9}$	$p_l^{\alpha=0.85}$	$p_m^{\alpha=0.85}$	$p_l^{\alpha=0.95}$	$p_m^{\alpha=0.95}$
X1.2.1.1, X2.1.1	Wind Conditions	0	0	0	0	0	0	0	0	0	0
X1.2.1.2.1, X2.1.2.2	Marine Icing	0	0	0	0	0	0	0	0	0	0
X1.2.1.2.2, X2.1.2.3	Sea Ice	0	0	0	0	0	0	0	0	0	0
X1.2.1.2.3, X2.1.2.3	Icebergs	1.14E-02	6.86E-03	1.14E-02	2.29E-02	1.10E-02	1.26E-02	1.07E-02	1.31E-02	1.12E-02	1.20E-02
X1.2.1.2.4, X2.1.2.4	Pressured Ice	0	0	0	0	0	0	0	0	0	0
X1.2.1.3, X2.1.3	Wave Conditions	0	0	0	0	0	0	0	0	0	0
X1.2.1.4, X2.1.4	Visibility	2.00E-03	1.20E-03	2.00E-03	4.00E-03	1.92E-03	2.20E-03	1.88E-03	2.30E-03	1.96E-03	2.10E-03

Table B7 July Fuzzy Basic Event Probabilities at Various α- cut Levels

						July					
Indicator	**Event Name**	**Basic Event Initial**	**Minimum Value**	**Most Likely**	**Max Value**	$p_l^{\alpha=0.9}$	$p_m^{\alpha=0.9}$	$p_l^{\alpha=0.85}$	$p_m^{\alpha=0.85}$	$p_l^{\alpha=0.95}$	$p_m^{\alpha=0.95}$
X1.2.1.1, X2.1.1	Wind Conditions	0	0	0	0	0	0	0	0	0	0
X1.2.1.2.1, X2.1.2.2	Marine Icing	0	0	0	0	0	0	0	0	0	0
X1.2.1.2.2, X2.1.2.3	Sea Ice	0	0	0	0	0	0	0	0	0	0
X1.2.1.2.3, X2.1.2.3	Icebergs	8.10E-03	4.86E-03	8.10E-03	1.62E-02	7.78E-03	8.91E-03	7.61E-03	9.31E-03	7.94E-03	8.50E-03
X1.2.1.2.4, X2.1.2.4	Pressured Ice	0	0	0	0	0	0	0	0	0	0
X1.2.1.3, X2.1.3	Wave Conditions	0	0	0	0	0	0	0	0	0	0
X1.2.1.4, X2.1.4	Visibility	3.00E-03	1.80E-03	3.00E-03	6.00E-03	2.88E-03	3.30E-03	2.82E-03	3.45E-03	2.94E-03	3.15E-03

Table B8 August Fuzzy Basic Event Probabilities at Various α- cut Levels

					August						
Indicator	**Event Name**	**Basic Event Initial**	**Minimum Value**	**Most Likely**	**Max Value**	$p_l^{\alpha=0.9}$	$p_m^{\alpha=0.9}$	$p_l^{\alpha=0.85}$	$p_m^{\alpha=0.85}$	$p_l^{\alpha=0.95}$	$p_m^{\alpha=0.95}$
X1.2.1.1, X2.1.1	Wind Conditions	0	0	0	0	0	0	0	0	0	0
X1.2.1.2.1, X2.1.2.2	Marine Icing	0	0	0	0	0	0	0	0	0	0
X1.2.1.2.2, X2.1.2.3	Sea Ice	0	0	0	0	0	0	0	0	0	0
X1.2.1.2.3, X2.1.2.3	Icebergs	1.23E-04	7.36E-05	1.23E-04	2.45E-04	1.18E-04	1.35E-04	1.15E-04	1.41E-04	1.20E-04	1.29E-04
X1.2.1.2.4, X2.1.2.4	Pressured Ice	0	0	0	0	0	0	0	0	0	0
X1.2.1.3, X2.1.3	Wave Conditions	0	0	0	0	0	0	0	0	0	0
X1.2.1.4, X2.1.4	Visibility	1.90E-03	1.14E-03	1.90E-03	3.80E-03	1.82E-03	2.09E-03	1.79E-03	2.19E-03	1.86E-03	2.00E-03

Table B9 September Fuzzy Basic Event Probabilities at Various α- cut Levels

				September							
Indicator	**Event Name**	**Basic Event Initial**	**Minimum Value**	**Most Likely**	**Max Value**	$p_l^{\alpha=0.9}$	$p_m^{\alpha=0.9}$	$p_l^{\alpha=0.85}$	$p_m^{\alpha=0.85}$	$p_l^{\alpha=0.95}$	$p_m^{\alpha=0.95}$
X1.2.1.1, X2.1.1	Wind Conditions	2.00E-03	1.20E-03	2.00E-03	4.00E-03	1.92E-03	2.20E-03	1.88E-03	2.30E-03	1.96E-03	2.10E-03
X1.2.1.2.1, X2.1.2.2	Marine Icing	0	0	0	0	0	0	0	0	0	0
X1.2.1.2.2, X2.1.2.3	Sea Ice	0	0	0	0	0	0	0	0	0	0
X1.2.1.2.3, X2.1.2.3	Icebergs	0	0	0	0	0	0	0	0	0	0
X1.2.1.2.4, X2.1.2.4	Pressured Ice	0	0	0	0	0	0	0	0	0	0
X1.2.1.3, X2.1.3	Wave Conditions	1.00E-03	6.00E-04	1.00E-03	2.00E-03	9.60E-04	1.10E-03	9.40E-04	1.15E-03	9.80E-04	1.05E-03
X1.2.1.4, X2.1.4	Visibility	1.00E-03	6.00E-04	1.00E-03	2.00E-03	9.60E-04	1.10E-03	9.40E-04	1.15E-03	9.80E-04	1.05E-03

Table B10 October Fuzzy Basic Event Probabilities at Various α- cut Levels

						October					
Indicator	**Event Name**	**Basic Event Initial**	**Minimum Value**	**Most Likely**	**Max Value**	$p_l^{\alpha=0.9}$	$p_m^{\alpha=0.9}$	$p_l^{\alpha=0.85}$	$p_m^{\alpha=0.85}$	$p_l^{\alpha=0.95}$	$p_m^{\alpha=0.95}$
X1.2.1.1, X2.1.1	Wind Conditions	3.00E-03	1.80E-03	3.00E-03	6.00E-03	2.88E-03	3.30E-03	2.82E-03	3.45E-03	2.94E-03	3.15E-03
X1.2.1.2.1, X2.1.2.2	Marine Icing	0	0	0	0	0	0	0	0	0	0
X1.2.1.2.2, X2.1.2.3	Sea Ice	0	0	0	0	0	0	0	0	0	0
X1.2.1.2.3, X2.1.2.3	Icebergs	0	0	0	0	0	0	0	0	0	0
X1.2.1.2.4, X2.1.2.4	Pressured Ice	0	0	0	0	0	0	0	0	0	0
X1.2.1.3, X2.1.3	Wave Conditions	1.00E-03	6.00E-04	1.00E-03	2.00E-03	9.60E-04	1.10E-03	9.40E-04	1.15E-03	9.80E-04	1.05E-03
X1.2.1.4, X2.1.4	Visibility	7.50E-04	4.50E-04	7.50E-04	1.50E-03	7.20E-04	8.25E-04	7.05E-04	8.63E-04	7.35E-04	7.88E-04

Table B11 November Fuzzy Basic Event Probabilities at Various α- cut Levels

						November					
Indicator	**Event Name**	**Basic Event Initial**	**Minimum Value**	**Most Likely**	**Max Value**	$p_l^{\alpha=0.9}$	$p_m^{\alpha=0.9}$	$p_l^{\alpha=0.85}$	$p_m^{\alpha=0.85}$	$p_l^{\alpha=0.95}$	$p_m^{\alpha=0.95}$
X1.2.1.1, X2.1.1	Wind Conditions	5.00E-03	3.00E-03	5.00E-03	1.00E-02	4.80E-03	5.50E-03	4.70E-03	5.75E-03	4.90E-03	5.25E-03
X1.2.1.2.1, X2.1.2.2	Marine Icing	0	0	0	0	0	0	0	0	0	0
X1.2.1.2.2, X2.1.2.3	Sea Ice	0	0	0	0	0	0	0	0	0	0
X1.2.1.2.3, X2.1.2.3	Icebergs	0	0	0	0	0	0	0	0	0	0
X1.2.1.2.4, X2.1.2.4	Pressured Ice	0	0	0	0	0	0	0	0	0	0
X1.2.1.3, X2.1.3	Wave Conditions	1.00E-03	6.00E-04	1.00E-03	2.00E-03	9.60E-04	1.10E-03	9.40E-04	1.15E-03	9.80E-04	1.05E-03
X1.2.1.4, X2.1.4	Visibility	9.00E-04	5.40E-04	9.00E-04	1.80E-03	8.64E-04	9.90E-04	8.46E-04	1.04E-03	8.82E-04	9.45E-04

Table B12 December Fuzzy Basic Event Probabilities at Various α- cut Levels

						December					
Indicator	**Event Name**	**Basic Event Initial**	**Minimum Value**	**Most Likely**	**Max Value**	$p_l^{\alpha=0.9}$	$p_m^{\alpha=0.9}$	$p_l^{\alpha=0.85}$	$p_m^{\alpha=0.85}$	$p_l^{\alpha=0.95}$	$p_m^{\alpha=0.95}$
X1.2.1.1, X2.1.1	Wind Conditions	1.00E-02	6.00E-03	1.00E-02	2.00E-02	9.60E-03	1.10E-02	9.40E-03	1.15E-02	9.80E-03	1.05E-02
X1.2.1.2.1, X2.1.2.2	Marine Icing	1.61E-04	9.68E-05	1.61E-04	3.23E-04	1.55E-04	1.77E-04	1.52E-04	1.85E-04	1.58E-04	1.69E-04
X1.2.1.2.2, X2.1.2.3	Sea Ice	0	0	0	0	0	0	0	0	0	0
X1.2.1.2.3, X2.1.2.3	Icebergs	0	0	0	0	0	0	0	0	0	0
X1.2.1.2.4, X2.1.2.4	Pressured Ice	0	0	0	0	0	0	0	0	0	0
X1.2.1.3, X2.1.3	Wave Conditions	3.00E-03	1.80E-03	3.00E-03	6.00E-03	2.88E-03	3.30E-03	2.82E-03	3.45E-03	2.94E-03	3.15E-03
X1.2.1.4, X2.1.4	Visibility	6.50E-04	3.90E-04	6.50E-04	1.30E-03	6.24E-04	7.15E-04	6.11E-04	7.48E-04	6.37E-04	6.83E-04

Appendix C – Refined Bayesian Network Posterior Probabilities

Table C1 Refined Bayesian Network Posterior Probabilities - January

January		
Event	**Prior Probability**	**Posterior Probability**
Collision	2.20E-03	4.85E-02
Grounding Failure	3.00E-05	6.62E-04
Engine Issues	2.60E-04	5.74E-03
Crew Availability	3.97E-04	8.76E-03
Fuel Availability	3.97E-04	8.76E-03
Navigation Equipment	2.55E-03	5.63E-02
Lifesaving Appliances	1.00E-03	2.21E-02
Firefighting Equipment	3.97E-04	8.76E-03
Operation System Failure	1.00E-04	2.21E-03
Navigation Failure	2.00E-06	4.41E-05
Software/Controls System Failure	4.00E-04	8.82E-03
Mechanical Failure (Communications)	1.00E-05	2.21E-04
Hull Integrity	1.33E-04	2.93E-03
Visibility	6.00E-04	1.32E-02
Wind Conditions	1.40E-02	3.09E-01
Sea Ice	6.67E-04	1.47E-02
Icebergs	0.00	0.00
Pressured Ice	1.67E-03	3.68E-02
Human Error	3.74E-02	8.27E-01

Table C2 Refined Bayesian Network Posterior Probabilities - February

	February	
Event	**Prior Probability**	**Posterior Probability**
Collision	2.20E-03	2.85E-02
Grounding Failure	3.00E-05	3.88E-04
Engine Issues	2.60E-04	3.37E-03
Crew Availability	3.97E-04	5.14E-03
Fuel Availability	3.97E-04	5.14E-03
Navigation Equipment	2.55E-03	3.30E-02
Lifesaving Appliances	1.00E-03	1.29E-02
Firefighting Equipment	3.97E-04	5.14E-03
Operation System Failure	1.00E-04	1.29E-03
Navigation Failure	2.00E-06	2.59E-05
Software/Controls System Failure	4.00E-04	5.18E-03
Mechanical Failure (Communications)	1.00E-05	1.29E-04
Hull Integrity	1.33E-04	1.72E-03
Visibility	9.00E-04	1.17E-02
Wind Conditions	1.70E-02	2.20E-01
Sea Ice	2.00E-02	2.59E-01
Icebergs	0.00	0.00
Pressured Ice	1.17E-02	1.51E-01
Human Error	6.96E-02	9.02E-01

Table C3 Refined Bayesian Network Posterior Probabilities - March

March		
Event	**Prior Probability**	**Posterior Probability**
Collision	2.20E-03	2.52E-02
Grounding Failure	3.00E-05	3.44E-04
Engine Issues	2.60E-04	2.98E-03
Crew Availability	3.97E-04	4.55E-03
Fuel Availability	3.97E-04	4.55E-03
Navigation Equipment	2.55E-03	2.92E-02
Lifesaving Appliances	1.00E-03	1.15E-02
Firefighting Equipment	3.97E-04	4.55E-03
Operation System Failure	1.00E-04	1.15E-03
Navigation Failure	2.00E-06	2.29E-05
Software/Controls System Failure	4.00E-04	4.59E-03
Mechanical Failure (Communications)	1.00E-05	1.15E-04
Hull Integrity	1.33E-04	1.52E-03
Visibility	9.50E-04	1.09E-02
Wind Conditions	4.00E-03	4.59E-02
Sea Ice	2.17E-02	2.49E-01
Icebergs	1.13E-02	1.30E-01
Pressured Ice	1.33E-02	1.52E-01
Human Error	6.86E-02	9.14E-01

Table C4 Refined Bayesian Network Posterior Probabilities - April

	April	
Event	**Prior Probability**	**Posterior Probability**
Collision	2.20E-03	2.95E-02
Grounding Failure	3.00E-05	4.03E-04
Engine Issues	2.60E-04	3.49E-03
Crew Availability	3.97E-04	5.33E-03
Fuel Availability	3.97E-04	5.33E-03
Navigation Equipment	2.55E-03	3.42E-02
Lifesaving Appliances	1.00E-03	1.34E-02
Firefighting Equipment	3.97E-04	5.33E-03
Operation System Failure	1.00E-04	1.34E-03
Navigation Failure	2.00E-06	2.68E-05
Software/Controls System Failure	4.00E-04	5.37E-03
Mechanical Failure (Communications)	1.00E-05	1.34E-04
Hull Integrity	1.33E-04	1.79E-03
Visibility	1.25E-03	1.68E-02
Wind Conditions	1.00E-03	1.34E-02
Sea Ice	1.50E-02	2.01E-01
Icebergs	2.21E-02	2.97E-01
Pressured Ice	8.33E-03	1.12E-01
Human Error	6.69E-02	8.98E-01

Table C5 Refined Bayesian Network Posterior Probabilities - May

	May	
Event	**Prior Probability**	**Posterior Probability**
Collision	2.20E-03	5.52E-02
Grounding Failure	3.00E-05	7.53E-04
Engine Issues	2.60E-04	6.53E-03
Crew Availability	3.97E-04	9.97E-03
Fuel Availability	3.97E-04	9.97E-03
Navigation Equipment	2.55E-03	6.40E-02
Lifesaving Appliances	1.00E-03	2.51E-02
Firefighting Equipment	3.97E-04	9.97E-03
Operation System Failure	1.00E-04	2.51E-03
Navigation Failure	2.00E-06	5.02E-05
Software/Controls System Failure	4.00E-04	1.00E-02
Mechanical Failure (Communications)	1.00E-05	2.51E-04
Hull Integrity	1.33E-04	3.34E-03
Visibility	1.50E-03	3.77E-02
Wind Conditions	0.00	0.00
Sea Ice	3.33E-03	8.36E-02
Icebergs	2.63E-02	6.60E-01
Pressured Ice	0.00	0.00
Human Error	3.19E-02	8.02E-01

Table C6 Refined Bayesian Network Posterior Probabilities - June

	June	
Event	**Prior Probability**	**Posterior Probability**
Collision	2.20E-03	1.01E-01
Grounding Failure	3.00E-05	1.38E-03
Engine Issues	2.60E-04	1.20E-02
Crew Availability	3.97E-04	1.83E-02
Fuel Availability	3.97E-04	1.83E-02
Navigation Equipment	2.55E-03	1.17E-01
Lifesaving Appliances	1.00E-03	4.61E-02
Firefighting Equipment	3.97E-04	1.83E-02
Operation System Failure	1.00E-04	4.61E-03
Navigation Failure	2.00E-06	9.21E-05
Software/Controls System Failure	4.00E-04	1.84E-02
Mechanical Failure (Communications)	1.00E-05	4.61E-04
Hull Integrity	1.33E-04	6.13E-03
Visibility	2.00E-03	9.21E-02
Wind Conditions	0.00	0.00
Sea Ice	0.00	0.00
Icebergs	1.14E-02	5.25E-01
Pressured Ice	0.00	0.00
Human Error	1.37E-02	6.30E-01

Table C7 Refined Bayesian Network Posterior Probabilities - July

	July	
Event	**Prior Probability**	**Posterior Probability**
Collision	2.20E-03	1.13E-01
Grounding Failure	3.00E-05	1.54E-03
Engine Issues	2.60E-04	1.34E-02
Crew Availability	3.97E-04	2.04E-02
Fuel Availability	3.97E-04	2.04E-02
Navigation Equipment	2.55E-03	1.31E-01
Lifesaving Appliances	1.00E-03	5.15E-02
Firefighting Equipment	3.97E-04	2.04E-02
Operation System Failure	1.00E-04	5.15E-03
Navigation Failure	2.00E-06	1.03E-04
Software/Controls System Failure	4.00E-04	2.06E-02
Mechanical Failure (Communications)	1.00E-05	5.15E-04
Hull Integrity	1.33E-04	6.85E-03
Visibility	3.00E-03	1.54E-01
Wind Conditions	0.00	0.00
Sea Ice	0.00	0.00
Icebergs	8.10E-03	4.17E-01
Pressured Ice	0.00	0.00
Human Error	1.14E-02	5.85E-01

Table C8 Refined Bayesian Network Posterior Probabilities - August

	August	
Event	**Prior Probability**	**Posterior Probability**
Collision	2.20E-03	2.10E-01
Grounding Failure	3.00E-05	2.87E-03
Engine Issues	2.60E-04	2.49E-02
Crew Availability	3.97E-04	3.80E-02
Fuel Availability	3.97E-04	3.80E-02
Navigation Equipment	2.55E-03	2.44E-01
Lifesaving Appliances	1.00E-03	9.57E-02
Firefighting Equipment	3.97E-04	3.80E-02
Operation System Failure	1.00E-04	9.57E-03
Navigation Failure	2.00E-06	1.91E-04
Software/Controls System Failure	4.00E-04	3.83E-02
Mechanical Failure (Communications)	1.00E-05	9.57E-04
Hull Integrity	1.33E-04	1.27E-02
Visibility	1.90E-03	1.82E-01
Wind Conditions	0.00	0.00
Sea Ice	0.00	0.00
Icebergs	1.23E-04	1.18E-02
Pressured Ice	0.00	0.00
Human Error	2.32E-03	2.22E-01

Table C9 Refined Bayesian Network Posterior Probabilities - September

	September	
Event	**Prior Probability**	**Posterior Probability**
Collision	2.20E-03	1.03E-01
Grounding Failure	3.00E-05	1.41E-03
Engine Issues	2.60E-04	1.22E-02
Crew Availability	3.97E-04	1.86E-02
Fuel Availability	3.97E-04	1.86E-02
Navigation Equipment	2.55E-03	1.20E-01
Lifesaving Appliances	1.00E-03	4.69E-02
Firefighting Equipment	3.97E-04	1.86E-02
Operation System Failure	1.00E-04	4.69E-03
Navigation Failure	2.00E-06	9.39E-05
Software/Controls System Failure	4.00E-04	1.88E-02
Mechanical Failure (Communications)	1.00E-05	4.69E-04
Hull Integrity	1.33E-04	6.24E-03
Visibility	1.00E-03	4.69E-02
Wind Conditions	2.00E-03	9.39E-02
Sea Ice	0.00	0.00
Icebergs	0.00	0.00
Pressured Ice	0.00	0.00
Human Error	1.33E-02	6.23E-01

Table C10 Refined Bayesian Network Posterior Probabilities - October

	October	
Event	**Prior Probability**	**Posterior Probability**
Collision	2.20E-03	9.98E-02
Grounding Failure	3.00E-05	1.36E-03
Engine Issues	2.60E-04	1.18E-02
Crew Availability	3.97E-04	1.80E-02
Fuel Availability	3.97E-04	1.80E-02
Navigation Equipment	2.55E-03	1.16E-01
Lifesaving Appliances	1.00E-03	4.54E-02
Firefighting Equipment	3.97E-04	1.80E-02
Operation System Failure	1.00E-04	4.54E-03
Navigation Failure	2.00E-06	9.07E-05
Software/Controls System Failure	4.00E-04	1.81E-02
Mechanical Failure (Communications)	1.00E-05	4.54E-04
Hull Integrity	1.33E-04	6.03E-03
Visibility	7.50E-04	3.40E-02
Wind Conditions	3.00E-03	1.36E-01
Sea Ice	0.00	0.00
Icebergs	0.00	0.00
Pressured Ice	0.00	0.00
Human Error	1.40E-02	6.35E-01

Table C11 Refined Bayesian Network Posterior Probabilities - November

November		
Event	**Prior Probability**	**Posterior Probability**
Collision	2.20E-03	9.11E-02
Grounding Failure	3.00E-05	1.24E-03
Engine Issues	2.60E-04	1.08E-02
Crew Availability	3.97E-04	1.64E-02
Fuel Availability	3.97E-04	1.64E-02
Navigation Equipment	2.55E-03	1.06E-01
Lifesaving Appliances	1.00E-03	4.14E-02
Firefighting Equipment	3.97E-04	1.64E-02
Operation System Failure	1.00E-04	4.14E-03
Navigation Failure	2.00E-06	8.28E-05
Software/Controls System Failure	4.00E-04	1.66E-02
Mechanical Failure (Communications)	1.00E-05	4.14E-04
Hull Integrity	1.33E-04	5.51E-03
Visibility	9.00E-04	3.73E-02
Wind Conditions	5.00E-03	2.07E-01
Sea Ice	0.00	0.00
Icebergs	0.00	0.00
Pressured Ice	0.00	0.00
Human Error	1.61E-02	6.68E-01

Table C12 Refined Bayesian Network Posterior Probabilities - December

December		
Event	**Prior Probability**	**Posterior Probability**
Collision	2.20E-03	6.51E-02
Grounding Failure	3.00E-05	8.87E-04
Engine Issues	2.60E-04	7.69E-03
Crew Availability	3.97E-04	1.17E-02
Fuel Availability	3.97E-04	1.17E-02
Navigation Equipment	2.55E-03	7.54E-02
Lifesaving Appliances	1.00E-03	2.96E-02
Firefighting Equipment	3.97E-04	1.17E-02
Operation System Failure	1.00E-04	2.96E-03
Navigation Failure	2.00E-06	5.92E-05
Software/Controls System Failure	4.00E-04	1.18E-02
Mechanical Failure (Communications)	1.00E-05	2.96E-04
Hull Integrity	1.33E-04	3.93E-03
Visibility	6.50E-04	1.92E-02
Wind Conditions	1.00E-02	2.96E-01
Sea Ice	0.00	0.00
Icebergs	0.00	0.00
Pressured Ice	0.00	0.00
Human Error	2.59E-02	7.65E-01