Operational risk assessment for shipping in Arctic waters

by

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Abstract

Arctic navigation has many complexities due to its particular features such as ice, severe weather conditions, remoteness, low temperatures, lack of crew experience, and extended period of darkness or daylight. For these reasons, vessels, such as oil tankers, dry cargo ships, offshore supply vessels, research vessels, and passenger ships operating in the Arctic waters may pose a high risk of collision with ice and other ships causing human casualties, environmental pollution and the loss of assets. This thesis presents a conceptual framework that is focused on collision modelling. In order to understand the process of risk escalation and to attempt a proactive approach in constituting the collision models for Arctic navigation, the present thesis identifies various risk factors that are involved in a collision. Furthermore, the thesis proposes the probabilistic framework tools that are based on the identified risk factors to estimate the risks of collision in the Artic. The proposed frameworks are used to model the collision based risk scenarios in the region. They are developed with the use of Bayesian Networks, the Nagel-Schreckenberg (NaSch), and Human Factor Analysis and Classification (HFACS) models. In the present thesis, the proposed models are theoretical in nature, but they can be useful in developing a collision monitoring system that provides a real time-estimate of collision probability that could help avoid collisions in the Arctic. Further, the estimated probabilities are also useful in decision making concerning safe independent and convoy operations in the region.

The proposed frameworks simplifies maritime accident modeling by developing a practical understanding of the role of physical environment, navigational and operational related aspects of ships, and human errors, such as individual lapses, management failures, organizational failures, and economic factors in the collision related accidents in the Arctic.

This research also identifies the macroscopic properties of maritime traffic flow and demonstrates how these properties influence collision properties. The thesis also presents an innovative accident model for ice-covered waters that estimates the collision probability and establishes the relationship between the macroscopic properties of the traffic flow with the contributory accidental risk factors in the region.

The main focus of the present thesis is, to better understand, communicate, and incorporate specific risk factors into the maritime risk assessment processes, involve shipping organizations to agree on best practice methodologies and make the data sources easily available, and modify the Arctic risk management processes by implementing effective risk assessment techniques and appropriate risk treatment.

Dedication

This thesis is dedicated to my beloved parents, my father, Professor Dr. Shafique Ali Khan (late) and my mother, Tanveer Pirzadi (late)

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In the name of Allah (the God), the Most Beneficent, the Most Merciful. All praise be to Allah (the God) alone, the Sustainer of all the worlds, most Compassionate, ever Merciful, and I send salutations upon His noble prophet Muhammad peace be upon him.

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List of Acronyms & Notations

A, B, C	Nodes in BN
$A_1, A_2, \ldots, A_n$	Parent nodes of node *A* in BN
ABS	American Bureau of Shipping
AHP	Analytical Hierarchal Process
AIS	Automatic Identification System
AIRSS	Arctic Ice Regime Shipping System
B	*Blowing snow*
BN or BBN	Bayesian Network/ Bayesian Belief Network
C, C1, C2, C3	Collision/Estimated collision probabilities
$Con_1, Con_2, Con_3, Con_4$	Concentration of ice types
CA	Cellular Automata
CF-HFACS	Human Factor Analysis and Classification System for military activities of the Canadian Armed Forces
D	*Darkness*
DAG	Directed Acyclic Graphs
DBN	Dynamic Bayesian Network
E	Dynamic evidence
ER	Evidential Reasoning
F	*Fog*
FI	Fast Ice
FFT	Fuzzy Fault Tree
FSA	Formal Safety Assessment
FY ice	First Year ice
G	Graph
H	High
HFACS	Human Factor Analysis and Classification System
HFACS-ATC	Human Factor Analysis and Classification System for Air Traffic Control system
HFACS-Coll	Human Factor Analysis and Classification System for Collisions

HFACS-Grounding	Human Factor Analysis and Classification System for grounding
HFACS-MA	Human Factor Analysis and Classification System for maritime accidents
HFACS-MCTAI	Human Factor Analysis and Classification-Marine Convoy Traffic and Accidents in Ice-covered waters
HFACS-RR	Human Factor Analysis and Classification for railway investigation
HFACS-SIBCI	Human Factor Analysis and Classification System-Ship-Icebreaker Collision in Ice-covered waters
I	*Ice*
IAM	Integrated Accident Model
IC	*Ice concentration*
ID	*Ice drift*
IF	Ice Floes
IMO	International Maritime Organization
IR	Ice Ridge
IS	*Ice strength*
ISM Code	International Safety Management Code
L	Low
L	*Low temperatures*
LRF	Lloyd's Register Foundation
LSA Code	International Life-saving Appliance Code
M	Medium
MFI	Medium First Year Ice
MTS	Maritime Transportation System
N	*Number of vehicle*
N	No
NI	New Ice
NTSB	National Transportation Safety Board
NaSch model	Nagel-Schrekenberg model
NPT	Node Probability Table
NSR	Northern Sea Route

OOBN	Object Oriented Bayesian Network
OI	Old Ice
P	*Poor visibility*
Polar Code	International Code for Ships Operating in Polar Waters
POLARIS	Polar Operational Limit Assessment Risk Indexing System
Prob	Probability
QRA	Quantitative Risk Assessment
R	Risk
RIO	Risk Index Outcome
RV_1, RV_2, RV_3, RV_4	Risk index values
S	*Speed of the vessel*
SOLAS	International Convention for Safety of Life at Sea
STCW	International Convention on Standards of Training, Certification, and Watchkeeping for seafarers
T	*Types of ice*
T_e	Number of iterations
t	Timestep
TFI	Thick First Year Ice
VTS	Vessel Traffic Service
W	*Weather*
X, Y, Z	Random variables
Y	Yes
P	Global density
$J(\rho)$	Global Flow
v_{max}	Maximum velocity
$p_{deceleration}$	Deceleration probability
$\rho_{critical\ density}$	Critical density
K	Minimum safe distance between two vehicles
D	Space between the *i* th and *(i+1)*th vehicle
v_n	Velocity of *n*th ship
d_n	Space that the *n*th ship gives to its preceding ship

v_p	Velocity of the preceding ship
$k_{safe,n}$	Minimum safe distance between the *n*th ship and the preceding ship p during a convoy
n	Number of sites
x_n	Location of the *n*th ship
F	flow
v	Mean velocity

Chapter 1

Introduction, overview, and co-authorship statement

1.1 Problem statement

Icy waters and extreme weather conditions such as long cold winters, short cool summers, poor visibility, strong winds, snowstorms, and long polar nights of the Arctic cause high-risk potential for a range of marine accidents in the region. Vessels operating in the Arctic are at risk of collision with ice or another vessel, causing damage, that vary from a minor hull deformation to ruptures. These damages could put lives, assets , and the environment at significant risk. Independent navigation in the Arctic is only possible during summers, which typically lasts for three to three and a half months. Icebreaker assistance is used for transportation in the remaining months.

The Arctic Climate Assessment (Hassol, 2004) states that the extent and the amount of ice in the Arctic region are decreasing. Also, due to the growing interest in marine resources in the Arctic such as fisheries, hydrocarbons, minerals, and tourism, and the potential for new shipping routes through the Arctic from Asia to Europe and North America, the opportunities for maritime activities in the Arctic are increasing (Eguíluz et al., 2016). Consequently, due to the limited experience of ship operators transporting in the Arctic (Smith, 2019a), the future may see an increase in the potential of ship accidents in the region and its impact on the environment.

This thesis focuses on accident prevention in Arctic waters. Accident prevention in the risk framework can be improved by reducing the accident probabilities. Consequently, risks related to vessels navigating in the Arctic environment are also reduced (Smith, 2019b). There are many factors such as ship design, human factors, organizational factors, environmental factors, and management practices and policies, that can increase accident prevention in the Arctic. The main goal of this thesis is to address the risk factors that are related to ship accidents such as ship-ice and ship-ship/icebreaker collision in the Arctic, and to develop risk assessment models to assess the risk of collision in the region. These models are helpful in reducing the likelihood of accidents and increase the accident prevention element in the region.

1.2 Overview of shipping safety and risk assessment

Risk can be recognized as the possibility of damage associated with an activity or the likelihood of the occurrence of an incident that could result in danger to life, property, and environment or could lead to commercial or legal disputes. The term risk assessment is different for different professionals, for example, in business, a professional manager will assess the risk and take safety precautions at all levels of business, which include the assessment and management of financial and commercial risks and the obtaining of insurance. Likewise, to a safety and quality assurance manager, risk assessment is the application of a systematic approach to hazards: (1) identification of hazards, (2) risk assessment i.e. evaluation of risks associated with the hazards, (c) evaluation of the likelihood of hazards and the magnitude of the possible consequences, (d) risk control options, and (e) Analysis of the effectiveness of control options (Wadhwa, 2017). Wadhwa (2017) also emphasized that a company with a good safety culture should aim for transparency of management and operational practices, and the minimization of known risks. The author further described that safety culture in any organization can be enhanced by regular audits, risk assessments and evaluations, and the implementation of plans that can control risk.

Safety in the shipping industry has been shaped through learning from accidents. A well-known example of this is the Exon Valdez oil spill. The extreme consequences that can arise from oil spills were better understood after this accident. Shipping regulators then decided to make double hull construction compulsory for all oil tankers. The double hull acts as an additional barrier between the punctured hull and an oil spill. In order to achieve safety in shipping, researchers usually evaluate risk factors for shipping accidents, conduct risk assessment studies, draw general conclusion about the risk, and adopt different techniques to lower the probability of accidents or to lower the probability of related consequences, or sometimes to lower both. For instance, Smith et al. (2015) in their study, presented a model that describes Arctic shipping accidents and their causation factors. The model identifies that an ability to intervene is an important element to reduce the probability of an accident and its severity. It identifies four factors i.e. external, organizational, direct, and operational that can influence Arctic shipping accidents, and three types of consequences: near misses, incidents, and accidents. The authors used the case studies of the Kolskaya and Kulluk accidents to explain their model. Similarly, (Kum & Sahin, 2015) proposed recommendations to reduce the occurrence probabilities of accidents e.g. collisions and groundings in the Arctic by applying the Fuzzy Fault Tree (FFT) analysis. Emergency preparedness also plays an important role in lessening the probability of consequences of accidents.

1.2.1 Quantitative risk assessment and Bayesian Network modeling

A quantitative risk assessment (QRA) is an effective tool to capture a broad picture of risk of accidents, as (a) in QRAs risk is usually described in terms of probabilities and expected values of hazards and, (b) it has the ability to treat uncertainties related to the risk obtained for the desired event (Flage and Aven 2009). Montewka et al. (2014) use the QRA approach to develop a proactive framework for estimating the risk of maritime transportation in the Gulf of Finland. The study focuses on ship-ship collision in an open sea involving RoPax vessels. The authors adopt Bayesian Network (BN) as a tool to model collision risk and quantify uncertainties of the model. Khakzad et al. (2013) in their study stated that BNs are preferred for their ability to model human and organizational factors, to model common causes of accidents, to evaluate risk control options (Mazaheri et al., 2014), and to evaluate mitigation measures. The application of the BNs has also been proposed to the IMO for the third step of Formal Safety Assessment (FSA), which is the risk control options (Hänninen et al. 2009). BNs have been used to examine many accident scenarios in the maritime domain, for instance,

- Khan et al. (2014) propose a cause-consequence based model using BNs. They estimate the probability of maritime accidents and their related consequences during navigation in Arctic waters. Zhang (2014) also concludes that BNs are beneficial to deal with uncertainties in maritime risk assessments because they can combine objective data with subjective knowledge.

- Zeng et al. (2014) indicate that the BN model can effectively address the problem of data deficiency and mutual dependency of incidents in risk analysis. It can also model the development process of unexpected hazards and provide decision support for risk mitigation.
- Fu et al. (2016) considered hydro-meteorological parameters, such as wind speed, air temperature, visibility, sea temperature, ice concentration, ice thickness, and wave height, and ship performance parameters, such as ship speed, and engine power, as risk influencing factors for Arctic navigation. By taking said influencing parameters as an input, the authors applied a BN to predict the probability of ship besetting in ice along the analyzed route. The results of the study suggested prior judgments of safety and sailing conditions are necessary for ice-going ships before sailing in Arctic waters.
- Baksh et al. (2018) have used BN to investigate the possibility of marine accidents, such as collision, foundering, and grounding along the Northern Sea Route (NSR). In the proposed risk model, the different operational and environmental factors are considered as the factors that affect shipping operations in the NSR. The authors have demonstrated the application of the model by taking a case study of an oil-tanker navigating the NSR. The case study indicated that collision, grounding, and foundering probabilities are high in the East Siberian Sea. The model suggested that the ice effect is a dominant factor in accident causation in the NSR.

- Zhang and Thai (2016) discussed some of the basic reasons to choose BNs for modeling maritime accidents, i.e. a clear presentation of causal relationships, making both forward and backward inferences, a combination of both experts' judgments and experimental data, its power to deal with uncertainty, and making updates with new information and observations. However, the difficulty in collecting the experts' opinions is one of the common challenges that researchers could have faced while using BNs for modeling maritime accidents.

Some researchers have investigated various human errors in marine accidents and linked them with the risk assessment studies, for instance,

- Hänninen and Kujala (2010) estimated the effect of the role of human factors in ship collision by means of BN. They consider data from the Gulf of Finland and identify the most plausible human factors affecting the BN.
- Hänninen et al. (2014) linked safety management to maritime traffic safety indicated by accident involvement, incidents reported by Vessel Traffic Service, and the results from Port State Control inspections. They use BN and the model parameters are based on expert elicitation and learning from historical data.
- Trucco et al. (2008) presented an innovative approach to integrating human and organizational factors into risk analysis. A BN is developed to model the Maritime Transport System (MTS) by considering its different actors (ship-owner, shipyard, port, and regulator) and their mutual influences. Conditional probabilities are estimated by means of experts' judgments collected from an

international panel. Finally, a sensitivity analysis is carried out to identify configurations of the MTS leading to a significant reduction of accident probability during the operation of a high-speed craft.

Though BN is identified as a useful and robust tool to model marine accidents, it does not account for the time dependence. To overcome this limitation of BN, dynamic BN (DBN) has been used in some accident modeling. DBN is a special form of BN that models the dynamics of the system by considering time. DBNs are the probabilistic graphical models that are used to describe the uncertainties of diverse situations. They can reduce the computational complexities, predict complex phenomena, and provide support to decision making in the scenario where data is not clear and variables are highly interlinked (Sarshar et al. 2013). Cai et al. (2013) used DBNs to assess the risk of human factors on offshore blowout and (Sarshar et al. 2013) used DBNs to model passengers' panic during a ship fire.

1.3 Ice navigation, convoy operations, ship domain, and Nagel-Schrekenberg (NaSch) model

1.3.1 Ice navigation: ship-ice collision

Ice is an obstacle to any ship, even an ice breaker (Canadian Coast Guard, 2012a). Therefore, before entering an ice zone, the Master should try to identify the ice conditions in a suitable period of time so that the vessel's speed can be adjusted accordingly and the further passages/routes can be chosen carefully based on the aware situations (House et al. 2016).

In general ice strength is dependent on many factors, for instance, types (age and deformation) of ice, thickness, temperature, porosity, salinity, density. The ice thickness and types are important factors of ship-ice collision during ice navigation. Kubat and Timco (2003) in their study, investigated 125 events of vessel damage in the Canadian Arctic and determined that most of the vessels were damaged due to the presence of multiyear ice. Similarly, Canadian Coast Guard (2012) and American Bureau of Shipping (ABS) advisory (2014) also stated that presence of thick first-year ice, old ice (second year and multiyear), ice floes, level ice, deforming sea ice, i.e., rafted ice, ridges, rubbles, and hummocks are hazardous for ice navigation. Pieces of floating ice/icebergs or other drifting ice features are also threating for ships navigating in ice-covered waters. To avoid the ice hazards, the effectiveness of radar and radio communications (between ship to regulating authority) is important for safe ice navigation (Canadian Coast Guard 2012; ABS advisory 2014). In addition to this, navigational lights, searchlights, and ice charts also contribute to avoiding such hazards (Canadian Coast Guard, 2012a).

1.3.2 Route planning and effective safety measures for safe ice navigation

Route planning and safety measures also contribute to safe ice navigation. Route planning in Canada is guided and controlled by the *Arctic Ice Regime Shipping System (AIRSS)*. *AIRSS* is a regulatory standard that provides a formula to calculate *Ice Numerals* for different ice cover. *Ice Numerals* are based on the known ice conditions of the region and the ice class of the vessel (Østreng et al., 2013). For the NSR, routing of the merchant's vessels is usually governed by icebreaker escort (ABS advisory, 2014). IMO has recently introduced the *Polar Operational Limit Assessment Risk Indexing System (POLARIS)* to guide decision-making related to route selection in Polar waters. *POLARIS* assesses the ice conditions based on a *Risk Index Outcome (RIO)* that can be calculated as follows:

$$RIO = (Con_{1\times}\ RV_1) + (Con_{2\times}\ RV_2) + (Con_{3\times}\ RV_3) + (Con_{4\times}\ RV_4) \quad (1.1)$$

where, Con_1, Con_2, Con_3, and Con_4 are the concentrations of ice types, and RV_1, RV_2, RV_3, and RV_4 are the corresponding risk index values for a give ice class. RVs are functions of ice-class, seasons, and operational state (independent navigation or icebreaker assistance). Positive *RIO* suggests an acceptable risk level where operations can proceed, while negative *RIO* suggests unacceptable risk levels where operations should not proceed (ABS advisory, 2016). For effective safety measures, it is required that a crew be fully aware of the risks of operating the vessels in ice infested waters, and with the emergency systems. Masters and officers should be fully aware of the limitations of the vessel, on the basis of which they can relate the capabilities of the vessel with the ice conditions (ABS advisory, 2009). It is mandatory that all the ice navigators onboard carry an operating manual and training manual concerning the effective safety at sea (Østreng et al., 2013).

1.3.3 Convoy operations: ship-ship/icebreaker collisions

Independent safe navigation in ice becomes difficult in winter, therefore, icebreaker assistance is sometimes necessary to help merchant vessels sailing through ice-covered waters. Goerlandt et al. (2017) discussed five practical operations with icebreaker assistance: (1) escorting, in which an icebreaker breaks a channel and a vessel follows the icebreaker at a distance, (2) breaking loose operations, in which icebreaker passes a ship that is beset in ice and breaks the ice at the sides and in front of the assisted ship, (3) convoy operations, are similar to escorting, however, in this case, several ships follow the icebreaker, (4) double convoy operations, in which one icebreaker moves a little ahead of the other icebreaker, to facilitate a vessel with a larger breadth than the icebreakers, and (5) towing operations, in which the assisted vessel is towed by the icebreaker because the channel has too much slush ice or the ice pressure makes the channel close too quickly.

Ship accidents occur more frequently in ice conditions than in open water (Goerlandt, Montewka, et al., 2017). Recent risk analysis studies suggested that during icebreaker operations, convoy operations are among the most hazardous situations in the wintertime conditions i.e. collision between the leading ship of a convoy and icebreaker and between the ships in a convoy are the most important related risk events (Valdez et al. 2015). Although crews in convoy operations are responsible for maintaining a safe distance between individual vessels in a convoy, the icebreaker crew may also advise the crew of assisted vessels regarding maintaining a safe distance between the vessels in a convoy. Compared to independent navigation, convoy operations require a highest speed of vessels to ensure efficient movement of ships in the convoy. The distance between the vessels in a convoy is important from a safety and operational perspective. If the distance between the two ships in a convoy is less than the safe distance, then a collision is more likely to occur, and if the distance between two ships in a convoy is longer than the safe distance, then the following ship may be hampered by the ice and consequently get stuck in ice (Goerlandt, Montewka, et al., 2017).

1.3.4 Ship domain

In marine convoy traffic, ships are required to maintain a safe zone between each other and between the icebreaker and the leading ship of the convoy, to avoid collisions. The required safe zone is known as the ship domain (Liu et al. 2016; Wang and Chin 2016; Fujii and Tanaka 1971; Toyoda and Fujii 1971; Wang 2013; Pietrzykowski and Uriasz 2009). The ship domain is used to define the safe distance between ships (Liu et al. 2010). According to recent research, the ship domain is dynamic (Liu et al. 2016; Wang and Chin 2016; Pietrzykowski and Uriasz 2009), as environmental conditions such as harsh weather and ice, velocity and size of ships, operational and navigational skills of the operator, and waterway conditions all are factors that can affect the size of ship domain (Qi et al. 2017).

1.3.5 Nagel-Schrekenberg (NaSch) model

Nagel-Schrekenberg (NaSch) model is a Cellular Automata (CA) model that is used to model single lane traffic. In this model, the velocity of the vehicle is gradually increased by one unit per time step (Nagel & Schreckenberg, 1992). It is also used to model freeway road traffic flow. It provides a basic understanding of traffic flow regarding global density, and global flows of the vehicle that help in avoiding congestion and collisions in the lanes. Wright (2013), describes the global density ρ and global flow $J(\rho)$ as follows

$$\rho = \frac{N}{n} = \frac{Number\ of\ vehicle}{number\ of\ sites} \tag{1.2}$$

$$J(\rho) = \frac{Number\ of\ vehicles\ passing\ a\ point}{number\ of\ timesteps} \tag{1.3}$$

The NaSch model is capable of incorporating with human behavior, which is a crucial factor when modeling traffic networks. It is a simple probabilistic CA model based on rule 184 (Wolfram 1986; Wright 2013). Rule 184 is a one-dimensional binary cellular automation rule; it forms the basis of many cellular automation models of traffic flow. In this model, particles that represent vehicles move in a single direction. Their starting and stopping depend on the vehicles in front of them (Wolfram, 1986). The number of particles remains unchanged during the simulation. The NaSch model is for single-lane traffic where vehicles cannot pass each other; there is no overtaking. Likewise, with a little updating in rules, the NaSch model can be used in maritime traffic flow (Rozkowsaka and Smolarek 2015; Qi, Zheng, and Gang 2017a; Qi, Zheng, and Gang 2017b; Liu et al. 2010; Feng 2013).

1.4 Human error and marine safety

Since shipping is the cheapest mode of transportation, over 90% of the world's cargo is transported by merchant vessels (Dhillon, 2007). Although modern ships contain many automated systems, still they require a significant human element. Humans are not hundred percent reliable, and studies have shown that about 75-96% of marine casualties are attributed due to some form of human error (Rothblum, 2000). According to Rothblum (2000), human errors are generally caused by design, environments, and organizations. The author further discussed that the physical environment causes stress and fatigue in crew, economic pressures can increase the probability of risk-taking, and organizational factors affect human performance. Examples are given here to exemplify human error and the related risk factors in marine industry.

- *Herald of Free Enterprise*: The accident occurred on 6th March 1987 due to the non-closure of the bow door by the assistant bosun who had fallen asleep. Consequently, 150 passengers and 38 crew members lost their lives in the accident. It was noted during the investigation that a few years earlier, a sister ship of the *Herald of Free Enterprise,* the *Pride of Free Enterprise* had sailed from Dover with all doors open due to the same reason which *Herald of Free Enterprise* had capsized. This shows that the organization completely failed to learn practically from the early incident. The careless attitude of the organization towards safety had been noticed during the investigation and this accident led towards an increased focus on the shipping company's role in accident causation and prevention (Manuel, 2011).
- *Green Lilly*: In November 1997, the vessel sailed into severe weather and grounded off the Shetland Islands. One life was lost, and the ship was a complete loss. The investigation report stated that the master did not receive any external pressure to sail in bad weather, but he decided to continue his journey to avoid delays (Manuel, 2011). The investigation report also stated that nobody from the crew openly questioned the master about his decision. Manuel (2011) also argued that lack of significant and obvious statements from the organization regarding "pressure not to sail" prioritize economy over safety.

- *Bow Mariner*: On 28th February 2004, the chemical tanker, *Bow Mariner,* caught fire during its tank-cleaning. The vessel exploded and sank about 45 nautical miles east of Virginia, USA. The accident led to the deaths of 3 crew members, 18 lost, and a release of cargo ethyl alcohol and fuel. The investigation report stated that it was the failure of the operator and the senior officers of the vessel, who could not properly implement the company policies of vessel safety. The lack of adequate communication and coordination between officers and crew members was also noticed during investigation, as the master, chief officer, and chief engineer all were Greek, and the remaining officers and crew members were Filipinos. It was observed that the chief officer, who was also the safety officer and responsible for equipment maintenance and training of personnel, had a lack of trust in his juniors. The surviving deck crew reported that the chief officer did not train his junior officers. Juniors with lack of training and fear of the senior officers could not question the master's order to open all empty tanks. The crew members either did not have an idea about the danger or they were not encouraged to question the master's order (Manuel, 2011).
- *Cruise Ship Norway*: On 25th May 2003, the boiler of the cruise ship ruptured resulting in the deaths of 8 crew members. The accident occurred due to technical reasons, but the investigation report highlighted that the owners of the ship were constantly warned by operators about lapses in the boiler maintenance (Manuel, 2011).

The errors that are observed in the above and other accident scenarios can be described as (1) Unsafe acts such as judgement failures, inadequate decisions, negligence, and inadequate general technical knowledge, (2) preconditions of unsafe acts such as poor weather, inadequate communication and coordination between crew members of a ship, crew members and the master of a ship, poor maintenance, navigational failures and fatigue, (3) unsafe supervision such as failure to continue safe operations and inadequate route planning, (4) organizational factors such as management practices and lack of training, and (5) external factors such as economic pressures and faulty company policies and standards. Human Factor Analysis and Classification System-HFACS frameworks (section 1.4.1) have been widely used in various industries to understand the role of latent and active errors in accidents. The early identification of errors in an organization can help to manage/reduce risks of accidents at the early stages.

1.4.1 Human Factor Analysis and Classification System-HFACS

Wiegmann and Shappell (2003) introduced HFACS in the aviation industry to analyze and classify human errors and mishaps in aviation accidents. An HFACS framework is specially developed to define the relevant active and latent failures in Reason's Swiss-cheese model. The model depicts the combination of active failures that are made by operators with the existing latent conditions in organizations. Active failures are the operator's actions and decisions that occur just before the accident and are often considered the most prominent cause of the accident. Latent failures are related to the organization i.e. decisions, conditions, policies, practices, and management that exist within the system for years but have never been associated with an accident or identified as a safety issue until they are overtly examined (Reinach and Viale 2006). It contains four layers of risk levels: (1) unsafe acts, (2) precondition for unsafe acts, (3) unsafe supervision, and (4) organizational factors together with 19 classifications. Reinach and Viale (2006) later proposed a fifth layer called the external factors. Authors believed that the economy, law, and policy should also be considered during the identification of accident risk factors. According to Zhang et al. (2019), the HFACS framework has been convincing for risk assessment studies because the factors of each layer can change continuously according to the object of research. The main advantage of HFACS is its use of common terms that apply to a variety of industries and activities (Reinach and Viale 2006). HFACS model was originally developed for the aviation industry. Since the model is reasonably flexible, minor changes can make it useable for other industries, such as marine and rail. The new taxonomies can have different names such as HFACS-ATC, for addressing the errors of air traffic control (Scarborough and Pounds 2001), CF-HFACS for military activities of Canadian Armed Forces (Wiegmann and Shappell 2003), HFACS-RR for railway investigation (Reinach and Viale 2006), and HFACS-MA, HFACS-Coll, HFACS-Grounding, and HFACS-SIBCI for maritime accidents investigations (Chen and Chou 2012; Chauvin et. al 2013; Mazaheri et al. 2015; Zhang et al. 2019). Chauvin et al. (2013) are the first who proposed the fifth layer called outside factors to HFACS for maritime accident investigations. Later, other authors have also used the five-layer HFACS models in their studies to identify the risk factors for maritime accidents (Mazaheri et al. 2015; Zhang et al. 2019).

1.5 Scope of work and contribution

One of the main contributions of this thesis is to identify the contributory risk factors related to Arctic navigation and develop the probabilistic framework tools to assess the risks of collision. Risk factors that have been used in this study are collected from previous accidental pieces of literature and case studies. HFACS-MCTAI has also been proposed in this study to identify and classify supervisory, organizational, and economy-related risk factors to assess the collision risk in the Arctic waters. The probabilities obtained from the proposed models can be used to develop an early warning system, due to which, vessels may get some time to slow down or divert away from the challenging area.

The proposed thesis is well in line with the Polar Code address i.e. the need for risk assessment tools for operations in polar waters. The proposed updated NaSch model provides a new perspective on the dynamics-related risk factors for Arctic navigation, for instance, risks related to the increased maximum velocities, high deceleration probabilities, and the reduced critical densities in the convoy. The integration of the updated NaSch model with the BN model simplifies maritime accident modeling by developing a practical understanding of the role of macroscopic properties such as, maximum velocities, deceleration probabilities, and critical densities of the traffic flow in maritime convoys. The integrated model also identifies the main risk factors for convoy traffic flow and can be used as a guiding tool to control and minimize the navigational and operational risks in the Arctic convoys.

The proposed HFACS-MCTAI framework identifies two new risk factors i.e. crew reduction and crew overloaded in its layer of organizational factors that do not influence the risk of collision directly but a small increase in the factors greatly influences the risk of an accident. Crew reductions are associated with technology implementation that results in the risks of crew overloaded. The crew overload can increase the risks of stress, fatigue, and boredom in the crew members, which will degrade the safety of the system at sea. The proposed study suggests that shipping organizations should understand that ships are sociotechnical systems based on technologies, crew members, organizational structures, and an external environment. Therefore, innovations in technologies should be accompanied by the appropriate training of crew members, organizational innovations, and ergonomic design. These approaches help reduce the potential problems of stress, fatigue, and boredom of crew members in ships.

The thesis is written in manuscript format. Four research articles were developed during this study. Table 1.1 describes the articles that have been written during this research. Table 1.1. also establishes the connection of these articles to the overall objectives and associated tasks of this research.

Table 1.1. Organization of the thesis.

Article titles	Research objectives	Associated Tasks
Chapter 2: An operational risk analysis tool to analyze marine transportation in Arctic waters	• The research objective of this chapter is to construct the ship-ice collision model to assess the risk of collision in Arctic waters.	• Identify risk factors for Arctic navigation • Constitute small conceptual component models Object-Oriented BNs (OOBNs) that are based on identified risk factors. • The constituted OOBNs form (1) Ship navigational system states, (2) Ship operational system states, (3) Weather system states, (4) Ice states, and (5) Human error. • Integrate all the constituted OOBN models to construct a ship-ice collision model. • Illustrate the model's utility by examining the day-to-day risk of a hypothetical oil tanker navigating from Murmansk to China. • Discuss the results, perform sensitivity and uncertainty analysis.
Chapter 3: A DBN model for ship-ice collision risk in the Arctic waters	• The research objective of this chapter is to dynamically assess the risk of ship-ice collision in Arctic waters.	• Identify the dynamic risk factors for Arctic navigation. • Construct a conceptual DBN model for Arctic waters based on the identified dynamic risk factors. • Illustrate the model's utility by examining the risk of a hypothetical oil-tanker navigating on the Barents Sea. • Discuss the results.
Chapter 4: A cellular automation model for convoy traffic in Arctic waters	• The research objective of this paper is to assess the risk of ship-ship and ship-ice breaker	• Update Nagel-Schreckenberg (NaSch) model to develop a collision accident model for marine convoy traffic in Arctic waters.

Article titles	Research objectives	Associated Tasks
	collision in a convoy while navigating in Arctic waters.	• Test the model on Vilkitskii strait and compute the critical density of the traffic flow. • Integrate the updated NaSch model with BN to develop a conceptual risk model in order to assess the risk of ship-ship/icebreaker collision in a convoy. • Discuss the results, perform sensitivity analysis.
Chapter 5: Integrated accident model for marine convoy traffic in ice-covered waters	• The research objective of this chapter is to develop a conceptual accident model for convoy traffic in ice-covered waters.	• Construct HFACS-Marine Convoy Traffic and Accidents in Ice-covered waters (HFACS-MCTAI) model. • Identify contributing risk factors and classify them on the basis of the HFACS-MCTAI model. • Develop the cause-consequences relationship between the contributory risk factors. • Develop a case study of winter navigation of hypothetical marine convoy traffic on the St. Lawrence Seaway and estimate the accident probabilities of risk factors, also estimate the critical density of the flow by using the updated NaSch model (developed in Chapter 4) • Integrate HFACS-MCTAI with an updated NaSch model using BN to develop an Integrated Accident Model (IAM). • Estimate the ship-ship/icebreaker collision and ship-ice collision probability. • Discuss the results, perform sensitivity analysis.

1.6 Novelty

- In this research, the OOBN technique has been employed to model maritime accident scenarios.
- The relationship between the physical environment, navigational and operational related aspects of ships and human errors such as individual management failures, organizational failures, and economic factors have been developed to model the ship-ice and ship-ship/icebreaker collision-based risk scenarios.
- DBN is used to model ship-ice collision. Until now, no attempts have been made to use DBN to model collision accident scenarios.
- Very few attempts have been made to use the Cellular Automata (CA) technique to model maritime accident scenarios. In this research, the CA framework is used to model collision risk scenarios in a marine convoy.
- The CA-based accident model has been integrated with BN to assess the risk of ship-ship/icebreaker collision in a convoy.
- The relationship between macroscopic properties of a convoy flow i.e. deceleration probability, maximum velocity, and critical density, and the factors for a convoy safety i.e. maintaining a safe distance between 2 ships in a convoy, maintaining a safe speed in ice, safe operations in ice, and maintaining a safe distance between an icebreaker and the leading ship of a convoy, have been developed.

- HFACS-Marine Convoy Traffic and Accidents in Ice-covered waters (HFACS-MCTAI) framework has been proposed in this study to classify the contributory risk factors for ship-ice and ship-ship/icebreaker collision in a convoy. For the very first time, the cause-consequence relationships between the classified contributory risk factors have been developed in this research.
- An Integrated Accident Model (IAM) for marine convoy traffic in ice-covered waters has been proposed. The model is constructed by integrating the HFACS-MCTAI framework with a CA-based accident model through BN. The IAM model is innovative. The main purpose of this model is to assess the risk of ship-ice and ship-ship/icebreaker collision in a convoy navigating in ice-covered waters. The IAM also establishes the relationship between the contributory accidental risk factors with the macroscopic properties of the convoy traffic flow.
- This research also demonstrates that the macroscopic properties of a convoy flow influence the collision probabilities.

1.7 Co-authorship statement

The author was responsible for composing this thesis. She conducted the literature review and developed all the accident models that are based on BN, OOBN, DBN, CA, and HFACS, respectively. The author produced the conceptual accident models of ship-ice and ship-ship/icebreaker collisions and tested them by considering case studies of oil-tanker or a marine convoy navigating in Northern Sea Route (NSR) and the ice-covered waters of North Atlantic Ocean. Conclusions were drawn based on the modeling results and its practical application. The co-authors Khan and Veitch provided feedback on draft versions of the four manuscripts.

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Chapter 2

An Operational Risk Analysis Tool to Analyze Marine Transportation in Arctic Waters[*]

Co-authorship statement. Co-authorship statement. A version of this chapter has appeared as an article in the journal titled *Reliability Engineering & System Safety* published by Elsevier. The lead author, Bushra Khan, has developed and implemented the Bayesian network-based model. She tested the model, analyzed its results and wrote the manuscript. The co-authors Dr. Faisal Khan, Dr. Brian Veitch, and Dr. Ming Yang supervised this study and made a technical contribution. All authors read and approved the final draft.

Abstract. The Arctic Ocean has drawn major attention in recent years due to its rich natural resources and shorter navigational routes. Arctic development and transportation involve significant risk caused by the unique features of this region, such as ice, severe operating conditions, unpredictable climatic changes, and remoteness. Considering the high degree of uncertainty in the performance of vessel operating systems and humans, robust risk analysis and management tools are required to provide decision-support to prevent accidents and ensure safety at sea. This paper proposes an OOBN model to dynamically predict ship-ice collision probability based on navigational and operational system states, weather and ice conditions, and human error. The model, when integrated with potential consequences, may help estimate risk. A case study related to oil tanker navigation on the Northern Sea Route (NSR) is used to show the application of the proposed model to predict oil tanker collision with sea ice.

[*] Khan, B, Khan, F., Veitch, B., and Yang, M. (2017). An Operational Risk Analysis Tool to Analyze Marine Transportation in Arctic Waters. *Reliability Engineering & System Safety* **169**, 485-502. https://doi.org/10.1016/j.ress.2017.09.014

2.1 Introduction

Marine transportation is an important service sector to support natural resource development and international commerce. Safety and efficiency are two critical concerns of the marine industry. The Arctic Climate Impact Assessment report (Hassol, 2004) states that the extent and the amount of ice in the Arctic region are decreasing. Therefore, forthcoming years may see reduced difficulty for marine transportation in Arctic waters. This may increase the potential of ship accidents in the region (Borgerson, 2008).

Navigation safety becomes a more critical issue considering various risk factors such as ice, severe operating conditions, unpredictable climatic changes, and remoteness. Also, the performance of vessel systems degrades in harsh environments, which consequently increases the risk of collision. (F. Khan et al., 2014) identified extremely low temperatures, multi-year sea-ice, ice-ridges, and pack-ice as the main causes of the increasing potential of ship accidents in the Arctic regions. Marchenko, Borch, Markov, and Andreassen (2015) have made similar conclusions. The authors mention that mineral exploration, fisheries, tourism, research, and naval operations are restricted due to the limited infrastructure, low temperatures, sea ice, icing, and polar lows. Human error is another main contributor to accidents (Rothblum, 2000). Li, Meng, and Qu (2012) summarize 87 academic research papers and project reports to analyze frequency and consequences-based risk estimation models separately. They argue that human error is of utmost importance in ship navigation and recommend more research in this field. The study by (Goerlandt & Montewka, 2015), discusses the scientific definitions and approaches related to maritime risk analysis and show that the probabilistic approach and the approaches based on realism and experiments are effective in this field.

A few recent attempts have been made to develop risk models for Arctic shipping, (Sahin & Kum, 2015) present various navigational risk factors in the Arctic ocean, determine the numerical weights for each risk factor using a Fuzzy-AHP approach, and calculate the risks with numerical probabilistic levels. Risk matrices are used to assess frequencies and consequences of grounding, collision (with sea ice and others), fire, violence or terror for various cruise ships, cargo, tankers, petroleum installations, and fishing boats in the Norwegian and the west Russian Arctic regions (Marchenko et al., 2015).

A quantitative risk assessment (QRA) is an effective tool to capture a broad picture of risk of accidents, as (a) in QRAs risk is usually described in terms of probabilities and expected values of hazards and, (b) it has the ability to treat uncertainties related to the risk obtained for the desired event (Flage & Aven, 2009). Risk has been defined as expected value, probability of an undesirable event, uncertainty, potential losses, probability and severity of consequences, event or consequences, consequences + uncertainty, and effect of uncertainty on objectives (Aven, 2012; Goerlandt & Montewka, 2015). Montewka et al. (2014) use the QRA approach to develop a proactive framework for estimating the risk of maritime transportation in the Gulf of Finland. This study focuses on ship-ship collision in an open sea involving RoPax vessels. They adopt Bayesian Belief Networks (BBN) as a tool to model collision risk and quantify the uncertainties of the model. To dynamically assess the transportation risk, Khan et al. (2014) propose a cause-consequence based model using Bayesian networks (BN). They estimate the probability of maritime accidents and their related consequences. Some hindrances to maritime risk assessments, such as missing data and fuzziness, are discussed in (D. Zhang, 2014). The author concludes that fuzzy logic, analytical hierarchal process (AHP), evidential reasoning (ER) and BNs are advantageous to deal with uncertainties because they can combine objective data with subjective knowledge. An approach to estimate the effect of the role of human factors in ship collision by means of BN is proposed by (Hänninen & Kujala, 2010). They consider data from the Gulf of Finland and discover the most plausible human factors affecting the BN. Hänninen, Valdez Banda, and Kujala (2014) link safety management to maritime traffic safety indicated by accident involvement, incidents reported by Vessel Traffic Service, and the results from Port State Control inspections. They use BN and the model parameters are based on expert elicitation and learning from historical data. An innovative approach to integrating human and organizational factors into risk analysis is presented by (Trucco et al., 2008). A BN is developed to model the Maritime Transport System (MTS) by considering its different actors (ship-owner, shipyard, port, and regulator) and their mutual influences. Conditional probabilities are estimated by means of experts' judgments collected from an international panel of different European countries. Finally, a sensitivity analysis is carried out to identify configurations of the MTS leading to a significant reduction of accident probability during the operation of a high-speed craft. The difficulty of risk analysis in RoPax transport is dealt by developing a BN that exploits expert surveys (Zeng et al., 2017). The results indicate that the BN model can effectively address the problem of data deficiency and mutual dependency of incidents in risk analysis. It can also model the development process of unexpected hazards and provide decision support for risk mitigation.

The above discussion indicates the usefulness of BN as an approach to model maritime risk. But some limitations with a standard BN representation make it difficult to learn, construct, update, infer and reason complex models. In this paper, we focus on key risk factors affecting safe navigation in the Arctic waters. Object-Oriented BN (OOBN) is proposed as an approach to model and analyze ship-ice collision accidents due to the following reasons:

(1) OOBNs are simple to construct, ready for reuse and flexible for modification,

(2) compared to standard BNs, their structure is less complex for better communication and explanation (Koller & Pfeffer, 1997), and

(3) they provide a modular approach such that evolving complexity in the model is effectively represented.

This paper aims to develop a quantitative risk assessment tool using Object Oriented BN to assess the probabilistic risk of ship-ice collision in Arctic waters. The model can be integrated with other decision support systems on corrective operational interventions. The remainder of the paper is structured as follows: Section 2.2 gives a brief overview of OOBNs, an OOBN based risk assessment methodology for ship-ice collision is proposed in Section 2.3; Section 2.4 presents an application of the proposed model through a case study that uses a hypothetical accident scenario related to oil tanker collision with ice along the NSR and discusses the results of a sensitivity analysis and the model's uncertainties. Section 2.5 concludes this study and proposes some future research directions.

2.2 Object-Oriented Bayesian Networks (OOBNs)

BNs become inefficient in two conditions: a) when a network includes so many nodes that understanding becomes difficult; and b) when a network includes many similar recurrent fragments. In both cases, it is difficult to comprehend the visual representation of (BNs). Therefore, in both cases, it is essential to decompose the network into smaller component models called OOBNs.

OOBNs have certain properties that are analogous to object-oriented modeling (Fenton & Neil, 2013). They can also be viewed as BNs with some added features that make them reusable as part of a larger BN. The most important feature of OOBN is its input and output nodes. OOBN follows the basic principles of object-oriented modeling, which are an abstraction, inheritance, and encapsulation (Blaha & Rumbaugh, 2004). The input/output nodes represent the "external interface" of OOBN. OOBN cannot produce more than one output for a single input. Also, they have ability to update the prior probabilities based on new information. Loops are not allowed; only forward propagation is allowed (Fenton & Neil, 2013).

In both standard BNs and OOBNs, the basic object is a standard random variable (nodes) (Koller & Pfeffer, 1997). A simple object is based on basic variables with Boolean, integer, and real type values, sometimes defined as enumerated sets. For example, *ice strength* $\in$ {high, medium, low}. A complex object comprises a set of attributes where each attribute itself is an object. They are composed of input, encapsulated (internal), and output nodes. An input node contains basic or structural variables, whereas encapsulated and output nodes are only simple objects. The

Table 2.1. Risk factors and their associated OOBNs in the ship-ice collision model

OOBN	*Risk factors*
Ship Navigational System States	Effective Radio Communication Radar Effectiveness Safe Maneuverability in Ice Covered Waters Use of Navigational lights and Search lights Ice Charts
Ship Operational System States	Effective Route Planning Effective Safety Measures Safe Operations in Ice Season Ship Class Speed
Weather System States	Blowing Snow Fog Long Polar Nights Visibility High Winds Seasons
Ice States	Ice Thickness Ice Types Ice Strength Pieces of Floating Ice/ Icebergs Drifting Ice
Human Error	Inadequate Technical Knowledge Inadequate Knowledge of own Ship System Decision based on Inadequate Information Inadequate Communication Fatigue

OOBNs presented here are all complex objects made up of input, encapsulated, and output nodes (see section 2.3.2).

2.3 The proposed methodology

Figure 2.1 presents the general framework of the proposed model. In the following sections, the main component of the proposed framework is discussed in detail.

2.3.1 Identification of main risk factors

The extreme weather conditions of the Arctic, along with the severe ice states, are unique environmental risk factors that may potentially cause accidental ship-ice collisions during vessel operation in the region. Other risk factors are related to

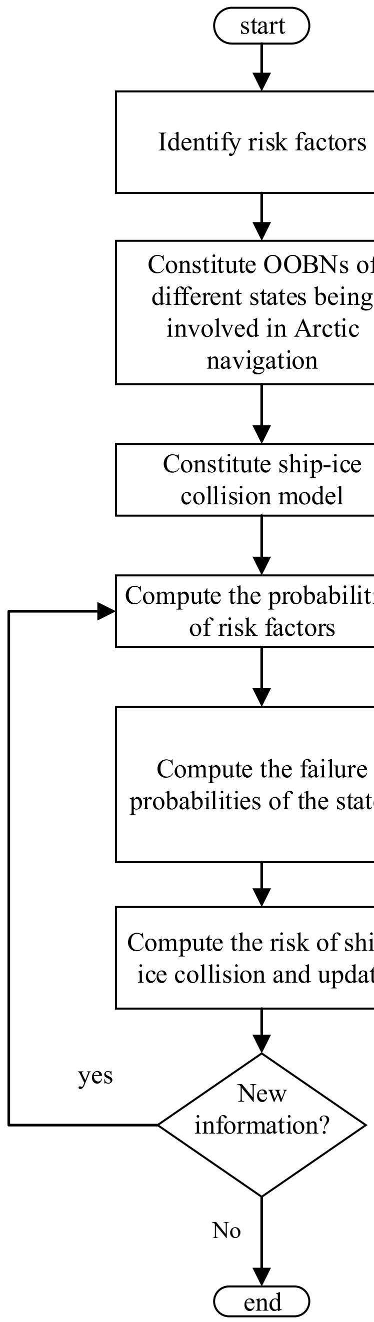

Figure 2.1. General framework of (OOBN) framework.

the vessel itself, such as ship navigational and operational systems. Human error is often a critical cause of a ship collision accident (Rothblum, 2000). Table 2.1 summarizes the risk factors for ship-ice collision accidents in Arctic waters. They were collected from various studies (ABS advisory, 2009, 2014; Bowditch, 2002; Canadian Coast Guard, 2012a; Environment-Canada, 2016; Rothblum, 2000; Sahin & Kum, 2015).

2.3.2 Construction of the OOBNs

Risk factors in Table 2.1 constitute small component models that are OOBNs: (a) *Ship Navigational System States*, (b) *Ship Operational System States*, (c) *Weather States*, (d) *Ice states*, and (e) *Human Error* (see Figures 2.2 to 2.6). The constituted OOBNs combine largely to constitute the (f) *Ship- Ice Collision* model in which all the output nodes of the preceding OOBNs turn into the input nodes (see Figure 2.7). The following explains the dependency among the nodes in the proposed OOBNs.

2.3.2.1 SHIP NAVIGATIONAL SYSTEM STATES

The effectiveness of radar and radio communications between ship to ship, ship to ice breakers and ship/icebreaker to regulating authority is important for safe maneuverability in ice-covered waters (ABS advisory, 2014; Canadian Coast Guard, 2012a). The conditional probability tables in current OOBN model are constructed as follows:

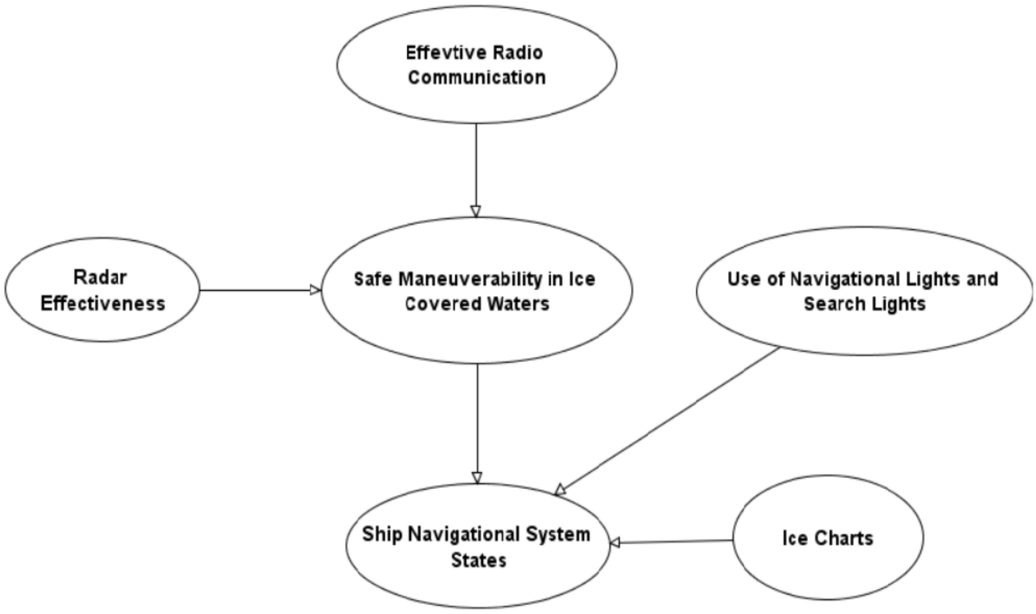

Figure 2.2. OOBN for Ship Navigational System States

Figure 2.3. OOBN for Ship Operational System States.

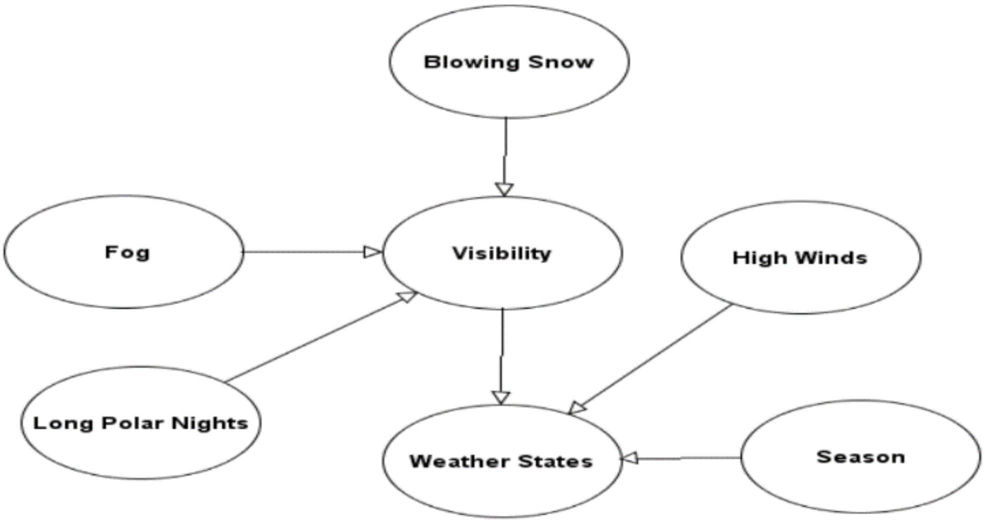

Figure 2.4. OOBN for Weather States.

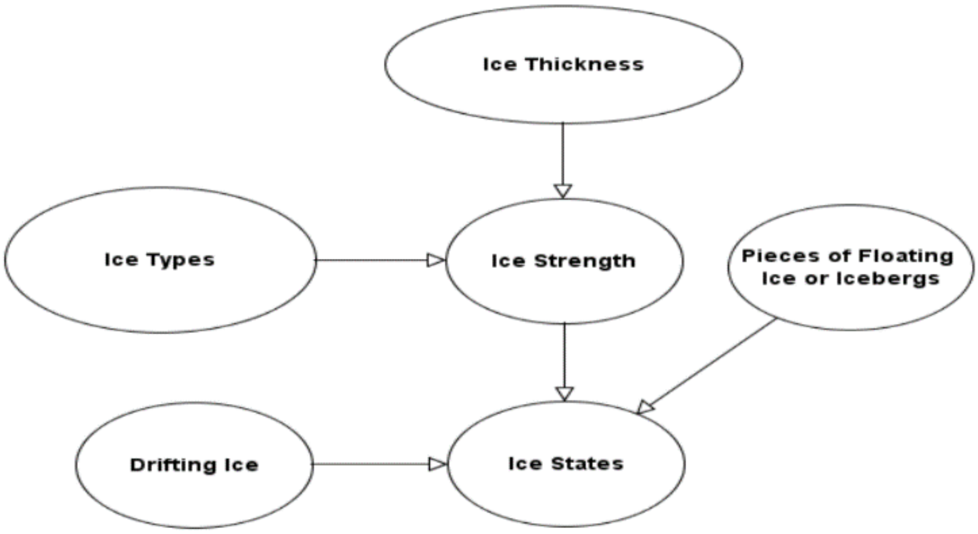

Figure 2.5. OOBN for Ice States.

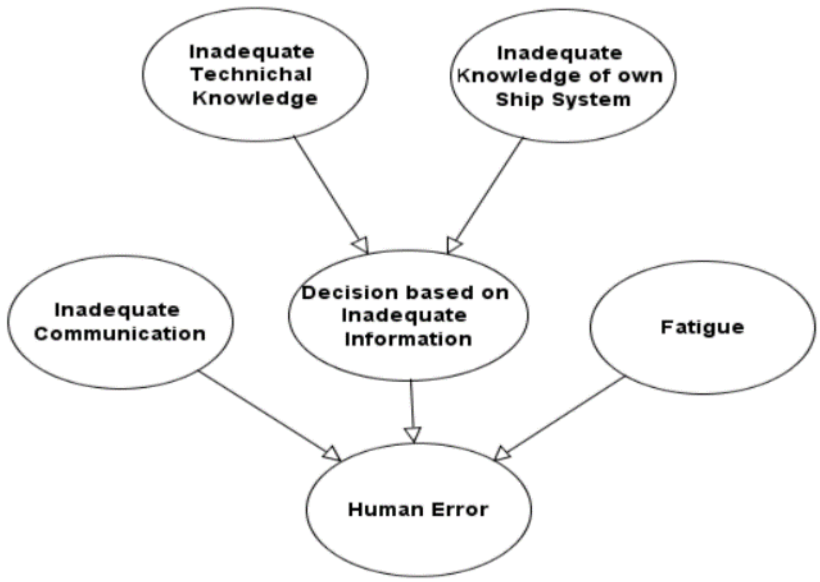

Figure 2.6. OOBN for Human Error.

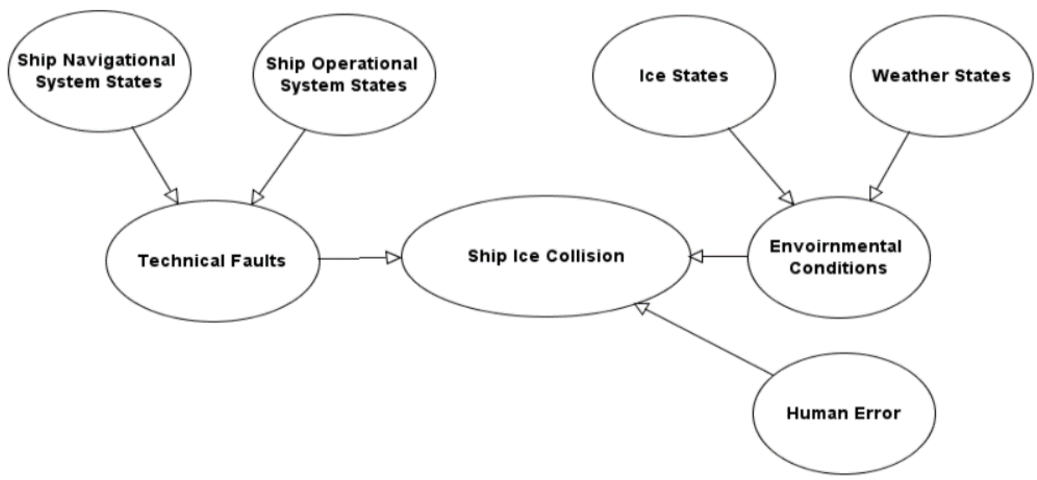

Figure 2.7. Ship-Ice Collision model.

(1) The internal node *Safe Maneuverability in Ice Covered Waters* is dependent on the input nodes: *Radar Effectiveness* and *Effective Radio Communication* (see Figure 2.2).

(2) The internal node also derives the output node, i.e., the *Ship Navigational System States* (see Figure 2.2).

(3) In addition to radar effectiveness and effective radio communication, navigational lights, search lights, and ice charts also contribute to safe ice navigation (Canadian Coast Guard, 2012a), therefore, the *Ship Navigational System States* is also dependent on another set of inputs defined by the nodes *Use of Navigational Lights and Search Lights* and *Ice Charts* (see Figure 2.2).

The node *Ship Navigational System States* is a Boolean node that takes values from the set {adequate, inadequate}.

2.3.2.2 Ship Operational System States

Route planning and safety measures make up the *Safe Operations in Ice node*. Route planning in Canada is guided and controlled by the *Arctic Ice Regime Shipping System (AIRSS)*. *AIRSS* is a regulatory standard that provides a formula to calculate *Ice Numerals* for different ice zones in the Canadian Arctic. *Ice Numerals* are based on the known ice conditions of the region and the ice classification of the vessel (Østreng et al., 2013). For the NSR, the routing of the merchant's vessels is usually governed by icebreaker escort (ABS advisory, 2014). IMO has recently introduced the *Polar Operational Limit Assessment Risk Indexing System (POLARIS)* to guide decision-making related to route selection in Polar waters. *POLARIS* assesses the ice conditions based on a *Risk Index Outcome (RIO)* that can be calculated as follows:

$$RIO = (Con_{1\times} RV_1) + (Con_{2\times} RV_2) + (Con_{3\times} RV_3) + (Con_{4\times} RV_4) \quad (2.1)$$

where, Con_1, Con_2, Con_3, and Con_4 are the concentrations of ice types, and RV_1, RV_2, RV_3, and RV_4 are the corresponding risk index values for a give ice class. RVs are functions of ice-class, seasons, and operational state (independent navigation or icebreaker assistance). Positive *RIO* suggests acceptable risk level where operations can proceed, while negative *RIO* suggests unacceptable risk levels where operations should not proceed (ABS advisory, 2016).

For effective safety measures, it is required that a crew be fully aware of the risks of operating the vessels in ice infested waters, and with the emergency systems. Masters and officers should be fully aware of the limitations of the vessel, on the basis of which they can relate the capabilities of the vessel with the ice conditions (ABS advisory, 2009). It is mandatory that all the ice navigators onboard carry an operating manual and training manual concerning the effective safety at sea (Østreng et al., 2013). IMO has implemented the *International Code for Ships Operating in Polar Waters (Polar Code)* which came into force in January 2017. The Polar Code deals with ship design, construction, and equipment, operational and training issues, search and rescue, and environmental protection of Polar waters and its related ecosystem (IMO, 2017).

Considering the factors *Effective Route Planning, Effective Safety Measures*, *Safe Operations in Ice*, *Seasons*, *Speed*, and *Ship Class*, the conditional probability tables in current OOBN model are constructed as follows:

(1) The internal node *Safe Operations in Ice* is dependent on *Effective Safety Measures,* and *Effective Route Planning.*
(2) *Ship Class* is dependent on *Seasons*
(3) The internal node also derives the output node *Ship Operational System States* which is dependent on *Speed,* and *Ship Class.*

Figure 2.3 shows a model of *Ship Operational System States*. The output node is a Boolean node with possible values from the set {good, poor}.

2.3.2.3 Weather States

Since, blowing snow, fog and long polar nights are the main factors to reduce visibility in the Arctic waters (Canadian Coast Guard, 2012a), we develop the OOBN model (see Figure 2.4) by keeping the *Visibility* as an internal node, the conditional probability tables in current OOBN model are constructed as follows:

(1) The internal node *Visibility* is dependent on the inputs *Blowing Snow, Fog,* and *Long Polar Nights* (see Figure 2.4).
(2) Later, the output node *Weather States* becomes dependent on the node *Visibility* in the model.
(3) The output node is also dependent on the inputs *High Winds* and the *Season.*

High winds are the principal factor of drifting ice and ice deformation at sea i.e. *Rafting, Ridging,* and *hammocking*, while *Seasons* have their own impacts on the weather e.g. the Arctic faces extremely rough weather in winter, mild in summer/spring and relatively harsh in Autumn. The output node takes values from the set {rough, normal, good}.

2.3.2.4 Ice States

While in general ice strength is dependent on many factors, for example, types (age and deformation) of ice, thickness, temperature, porosity, salinity, density. The ice thickness and types account for ice strengthening in the sea and hence considered as the most common factors of accidents. For instance, Kubat and Timco (2003) show in their study by analyzing 125 events of vessel damage in Canadian Arctic that most of the vessels were damaged due to the presence of multiyear ice. Similarly, Canadian Coast Guard (2012) and ABS advisory (2014) are also stated that presence of *Thick First Year Ice, Old Ice* (*Second Year* and *Multiyear*)*, Ice floes, Level Ice, Deforming Sea Ice,* i.e., *Rafted ice, Ridges, Rubbles and Hummocks* are significantly hazardous for navigation. The conditional probability tables in current OOBN model are constructed as follows:

(1) The model in Figure 2.5 defines the inputs by *Ice Thickness* and *Ice Types* which derive the node *Ice Strength*.
(2) *Ice Strength* is an internal node that also derives the output node *Ice States*.
(3) Since pieces of floating ice/icebergs or other drifting ice features are also the major threats to vessel operations in the Arctic, therefore, the model also shows the dependency of the output node on another set of input nodes: *Pieces of Floating Ice/ Icebergs* and *Drifting Ice*.

The output node, *Ice States,* takes values from the set {low, medium, high}.

2.3.2.5 Human Error

Rothblum (2000) argues that most marine accidents are caused by human mistakes: *Fatigue, Inadequate Communication*, *Inadequate Technical Knowledge*, *Inadequate Knowledge of Own Ship System*, and *Decisions based on Inadequate Information* are the main human-related issues in the marine industry. Figure 2.6 proposes a model of *Human Error*. The conditional probability tables in current OOBN model are constructed as follows:

(1) The internal node *Decisions based on Inadequate Information* is dependent on the inputs *Inadequate Technical Knowledge* and *Inadequate Knowledge of Own Ship Systems*.

(2) Later, the node *Human Error* is dependent on the said internal node. Research and surveys have identified that fatigue is the main problem in maritime industry (Margetts, 1976; National Research Council, 1990; NTSB, 1981; United States Coast Guard, 1995).

(3) However, National Transportation Safety Board (NTSB) (1981) also suggests improving the communication between shipmates and crew members, ship to ship, masters to pilots, and ship to VTS on board. Therefore, *Human Error* is also dependent on another set of inputs in the model i.e. the *Inadequate Communication* and the *Fatigue.*

Human Error is a Boolean node that takes values of the form yes/no.

2.3.2.6 Ship-Ice Collision

The *Ship Navigational System States* and the *Operational Systems States* are the main factors that define the ship's technical strength during navigation (Canadian Coast

Guard, 2012a; Valdez Banda et al., 2015). Therefore, minor negligence can cause a major fault in ships in the course of safe operations in ice. However, the combined effect of high *Ice States* and rough *Weather States* is responsible for the various anomalies in the environmental conditions in Arctic (Canadian Coast Guard, 2012a).

The model in Figure 2.7 explicitly combines all the preceding OOBNs to form a larger model for *Ship-Ice Collision*. The outputs of preceding OOBNs, i.e., *Ship Navigational System States, Operational System States, Ice States, Weather States,* and *Human Error* are taken to be inputs in the proposed model (see Figure 2.7). The first internal node, *Technical Faults*, is dependent on *Ship Navigational System States* and *Operational System States*. The second internal node is *Environmental Conditions*, which is derived from the input nodes *Ice States,* and Weather *States*. The output node, *Ship-Ice Collision* is dependent on *Technical Faults*, *Environmental Conditions,* and *Human Error* because of obvious relationship of technical aspects, human fallibility, and environmental states with ship-ice collisions. The output node takes values of the form yes or no.

2.3.3 Model Update

The prior probabilities in the OOBNs (Figures 2.2-2.7) are updated continuously as new information becomes available. Figure 2.8 shows that all the individual OOBNs in the study are linked and embedded in the higher-level model. The higher-level model, particularly, specifies the input/output nodes by keeping the internal nodes encapsulated. This model has the ability to update simply by adding or subtracting any input/output nodes.

2.4 Case Study

2.4.1 Case Description

The proposed OOBN-based methodology is applied to an accident scenario to analyze the risk of oil tanker-ice collision in NSR. A hypothetical oil tanker is assumed to navigate from Murmansk to China (see Figure 2.9). It follows a route from the Kara Sea to the Laptev Sea and then to the East Siberian sea, defined by the administration of NSR (Arctic-Portal-Library, 2011). The major portion of the route is constrained by ice for much of the year. It becomes an ice-free zone only in summer. Severe weather conditions are other obstacles for marine transportation in NSR.

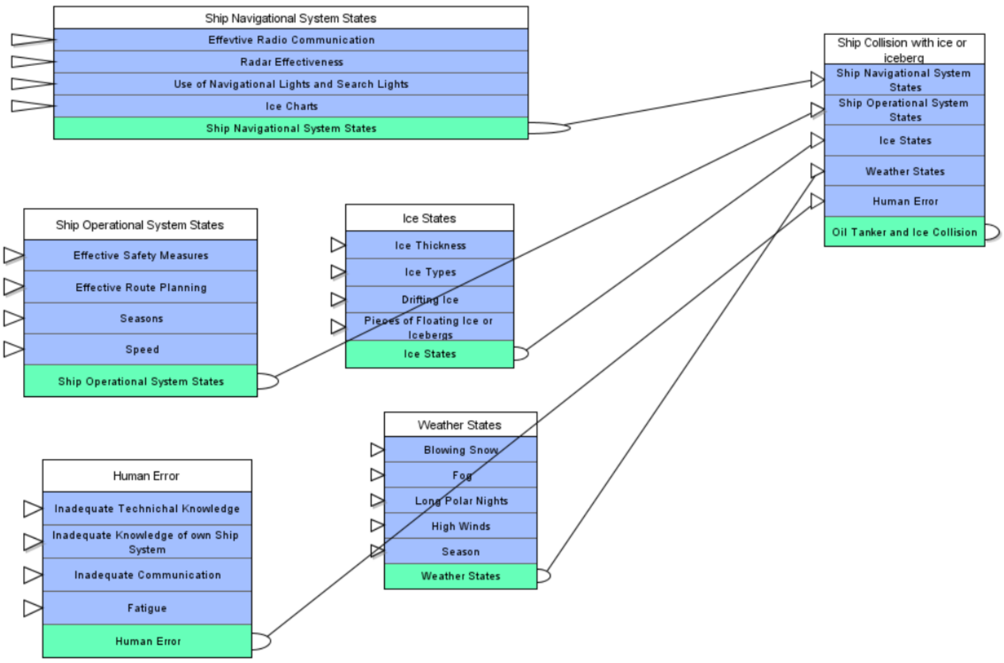

Figure 2.8. The complete top-level view of the Ship-Ice Collision model.

The model examines the day-to-day risk of tanker-ice collision. The total duration of the journey is around thirty days. Figures 2.10-2.15 illustrate the computational process. As the tanker proceeds in its journey through the NSR, the probabilities are updated given various evidence accumulated each day. The tool AgenaRisk (2016) is used in this study to develop all OOBNs and perform the computation.

Figures 2.10-2.15 demonstrate the OOBN process for day 1. Similar arguments hold for the other days (see Table 2.2).

Figure 2.9. Ship route from Murmansk to China.

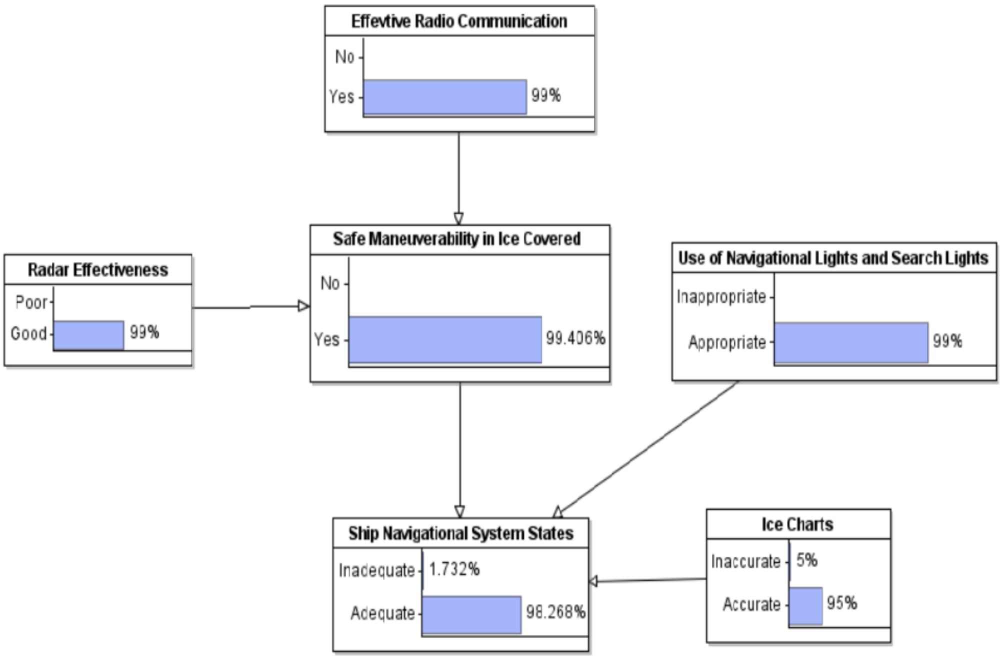

Figure 2.10. The probability of inadequate Ship Navigational System States in NSR for day 1.

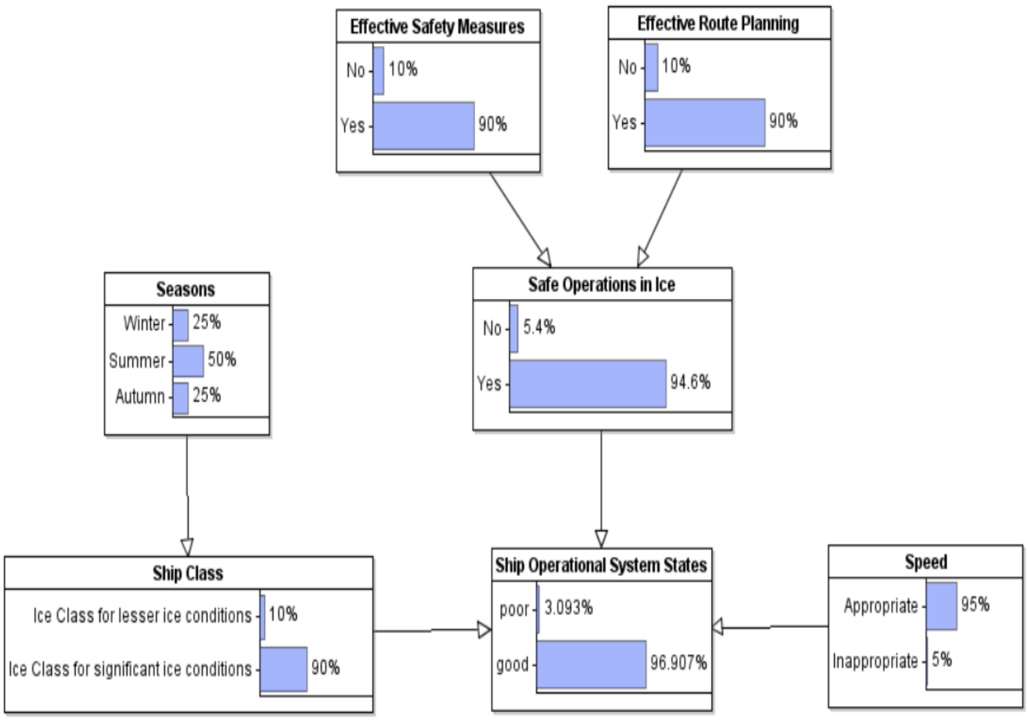

Figure 2.11. The probability of poor Ship Operational System States in NSR for day 1.

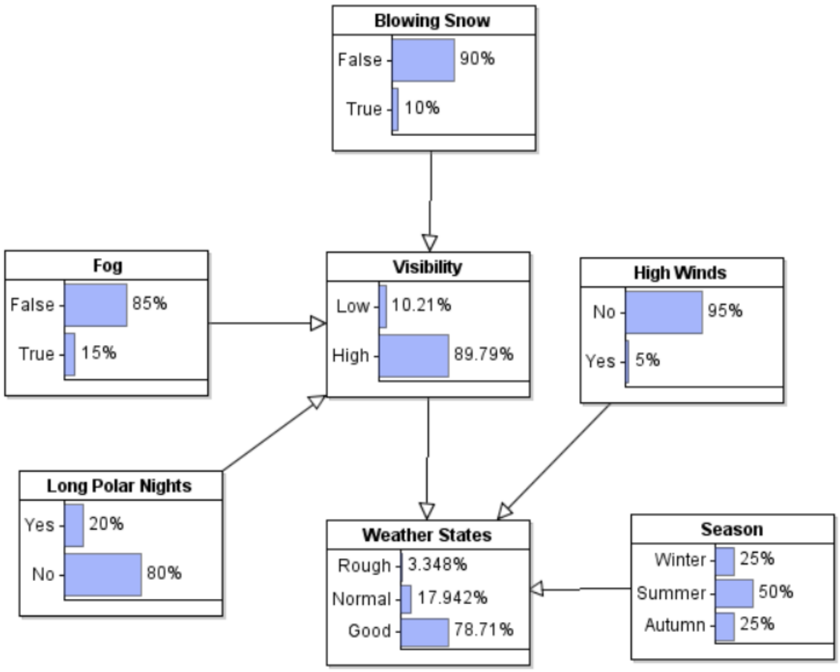

Figure 2.12. The probability of rough Weather States in NSR for day 1.

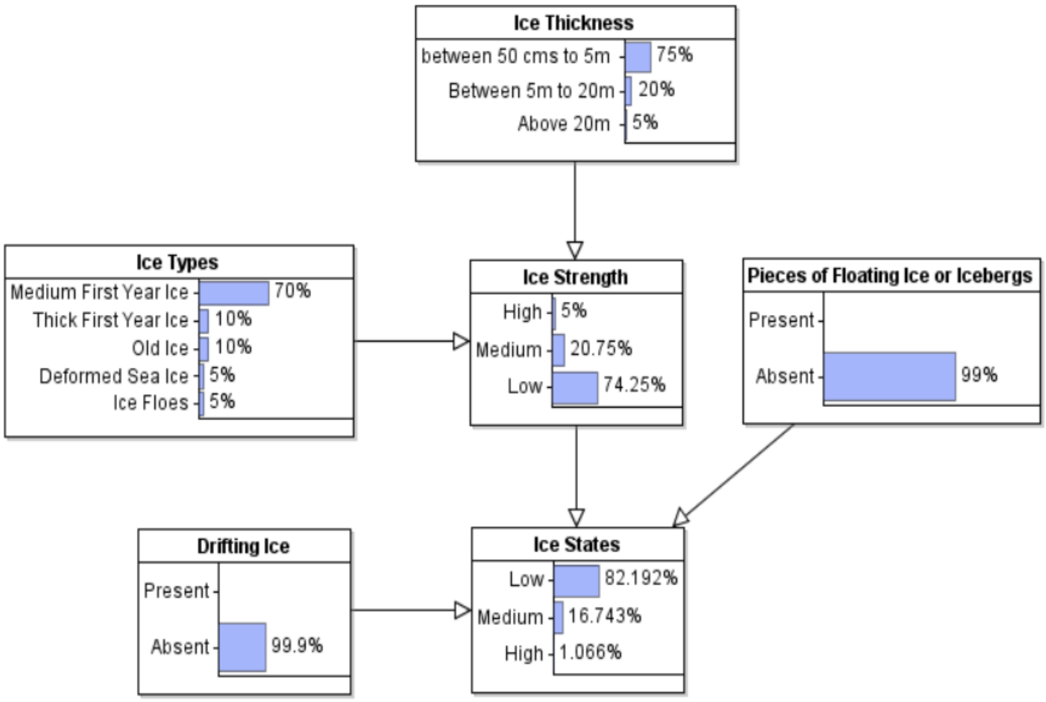

Figure 2.13. The probability of severe Ice States in NSR for day 1.

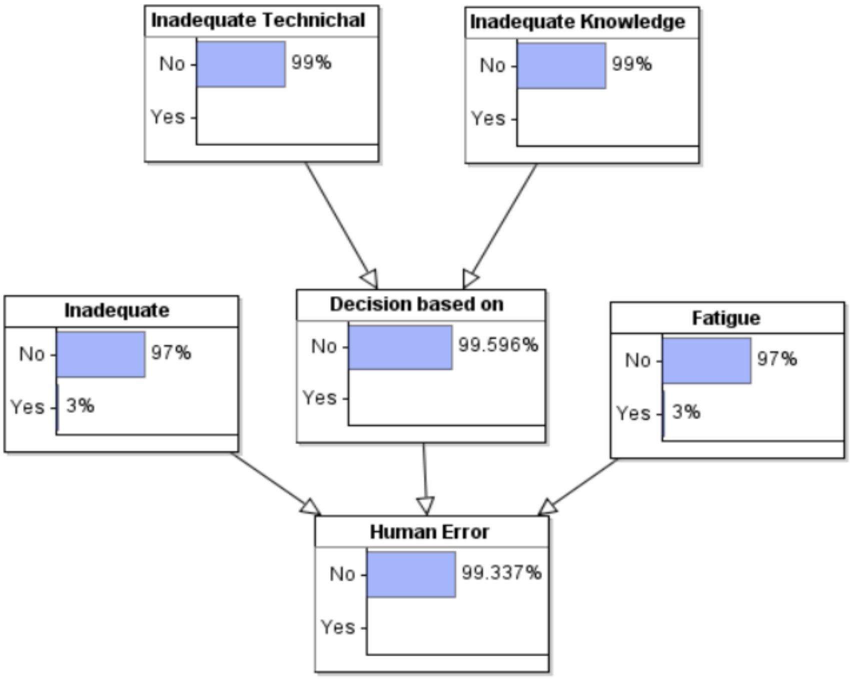

Figure 2.14: The probability of possible Human Error during the journey in NSR for day 1.

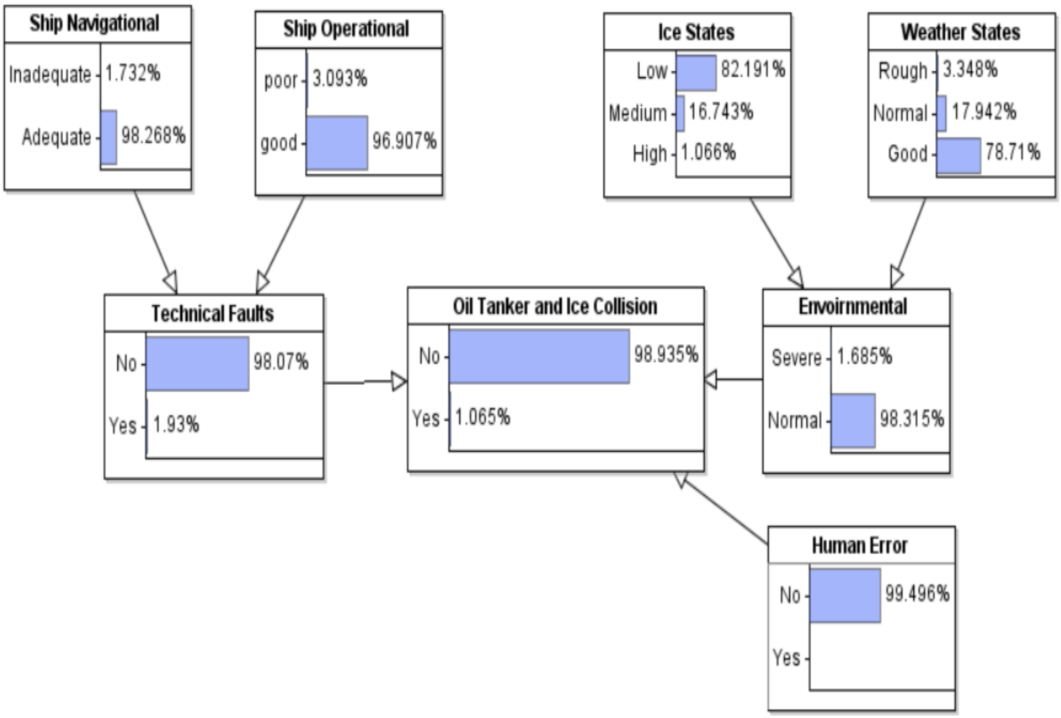

Figure 2.15. Risk of Oil Tanker-Ice Collision in NSR for day 1.

Table 2.2. Failure probabilities of the States and the risk of Oil Tanker-Ice collision in NSR.

Days	Inadequate Ship Navigational System States	Poor Ship Operational System States	Rough Weather States	Severe Ice States	Possible Human Error	Risk of Collision
1	0.01732	0.03093	0.03348	0.01066	0.00532	0.01065
2	0.02194	0.03377	0.03813	0.01131	0.00610	0.01227
3	0.02194	0.03377	0.04252	0.01134	0.00610	0.01261
4	0.02345	0.03377	0.04252	0.01134	0.00610	0.01279
5	0.02345	0.03377	0.02534	0.01134	0.00610	0.01148
6	0.02345	0.03581	0.02534	0.01134	0.00610	0.01171
7	0.02496	0.03581	0.02994	0.01323	0.00822	0.01299
8	0.02496	0.03581	0.03456	0.01323	0.00822	0.01334
9	0.02496	0.03581	0.03456	0.01373	0.00822	0.01337
10	0.02496	0.03581	0.03456	0.01377	0.00822	0.01338
11	0.02496	0.03581	0.04032	0.01413	0.00822	0.01385
12	0.02496	0.03581	0.05905	0.01413	0.00822	0.01537
13	0.02496	0.03581	0.05905	0.04819	0.00822	0.01736
14	0.02496	0.03863	0.05905	0.04819	0.00822	0.01769
15	0.02619	0.03863	0.05905	0.04819	0.00822	0.01784
16	0.02619	0.03863	0.05905	0.05103	0.00822	0.01811
17	0.02619	0.03863	0.05905	0.05538	0.00822	0.01839
18	0.02619	0.03863	0.05905	0.05538	0.01033	0.01902
19	0.02619*	0.03863	0.08247	0.05538	0.01033	0.02084*
20	0.02619	0.03863	0.08247*	0.05538*	0.01091	0.02102*
21	0.02619	0.03863*	0.08247	0.05117	0.01091	0.02077*
22	0.02619	0.03863	0.08247	0.04991	0.01091*	0.02068*
23	0.02619	0.03863	0.03564	0.04991	0.01091	0.01711
24	0.02619	0.03863	0.03348	0.04991	0.01091	0.01692
25	0.02375	0.03863	0.03348	0.04991	0.01091	0.01674
26	0.01494	0.03863	0.03348	0.04991	0.01091	0.01569
27	0.01494	0.03863	0.03348	0.02498	0.01091	0.01403
28	0.01494	0.03300	0.03348	0.02498	0.01091	0.01338
29	0.01494	0.02454	0.03348	0.02498	0.00663	0.01109
30	0.01494	0.02454	0.03348	0.02000	0.00663	0.01073

* The corresponding adjusted values are plotted in Figure 2.16 for making change in the tanker course

2.4.2 Results and discussions

The analysis indicates that the voyage during the 19th, 20th, 21st and 22nd days of the journey are riskier than the rest of the days. The respective probabilities of collision are beyond the assumed acceptable risk level of 2 percent. To reduce the expected risk, the route of the tanker for these four days is adjusted and consequently, the selected values of some risk factors in the model are also changed. The solid line in Figure 2.16 shows the risk profile of the adjusted route of the journey. Table 2.2 and Figure 2.16 demonstrates that the initial days of the tanker course are less hazardous than the mid-voyage, while the last ten days turn out to be again less risky.

Arbitrary data is used in this study for illustrative purposes only. A different set of values would give different results. The main advantage of using OOBN methodology is that it decomposes a complex system into small and reasonably concise components. Each component is reusable and can be modified separately without affecting the other components. For instance, the values referenced in the footnote of Table 2.2 are adjusted without altering any other component in the model. These important characteristics of OOBNs make it more advantageous than standard BNs (see Figure 2.17). In standard BNs, a large portion of the network may need to be modified for a minor modification, such as adding or deleting a node. Since the node "*Radar Effectiveness"* is removed from one of the components of *Oil Tanker -Ice Collision Model* (see Figure 2.18), the removal did not require any changes in the rest of the model (see Figure 2.19). However, if the same node is deleted from the regular BN model of *Oil Tanker-Ice Collision*, its linked nodes i.e. *Safe Maneuverability in Ice Covered Waters*", "*Effective Radio Communication*" and "*High Winds*" should also be deleted from the model (see Figure 2.20). While, this deletion involves significant modifications in the remaining model, which is a lengthy and error-prone procedure.

2.4.2.1 Sensitivity Analysis

The proposed methodology also makes it simple to perform root cause and sensitivity analyses for each main risk factor separately (see Tables 2.3-2.8). AgenaRisk is used to develop all the OOBNs in this study. It is also used to analyze the sensitivity of the risk factors included in the developed OOBNs.

Table 2.3 shows that the failures of the *"Safe Maneuverability in Ice Covered Waters"*, *"Use Navigational Lights and Search Lights"*, and *"Ice Charts"* impact significantly on *"Ship Navigational System States"* during the journey in NSR. Table 2.4 shows that the failure in maintaining the *"Safe Operations in Ice"*, *"Speed"*, and *"Effective Safety Measures"* are responsible for poor *"Ship Operational System States"* in NSR. Table 2.5 shows that the *"High Winds"*, *"Visibility"*, and *"Fog"* are

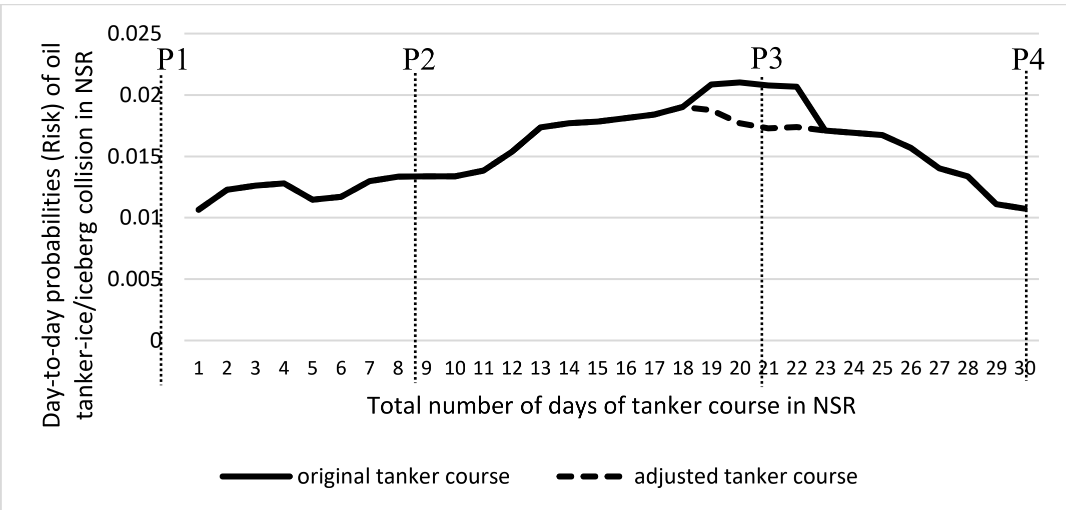

Figure 2.16. Day wise probabilistic (Risk) analysis of tanker collision in NSR. P1 is the position of the ship at the port of Murmansk, P2 refers to the port of Dikson (Kara Sea), P3 is the location of the port of Tiksi (Laptev Sea) and P4 is the port of Pevek in East Siberian region.

responsible for the rough *"Weather System States"* in NSR. Table 2.6 shows that the *"Ice Strength",* and *"Ice Thickness"* equivalently account for the high *"Ice States"* in NSR. Table 2.7 shows that the *"Decision based on Inadequate Information", "Inadequate Communication",* and *"Fatigue"* contribute equally to the *"Human Error"* being affirmative in NSR. Table 2.8 shows that the "*Human Error"* has the greatest impact on "*Oil Tanker-Ice Collision"* in NSR. This result matches the conclusions of (S. Li et al., 2012) and (Rothblum, 2000). They claim that *Human Error* is the most important factor contributing to marine accidents. Table 2.8 further shows that "*Technical Faults"* are the next to *Human Error* in *Oil Tanker-Ice*

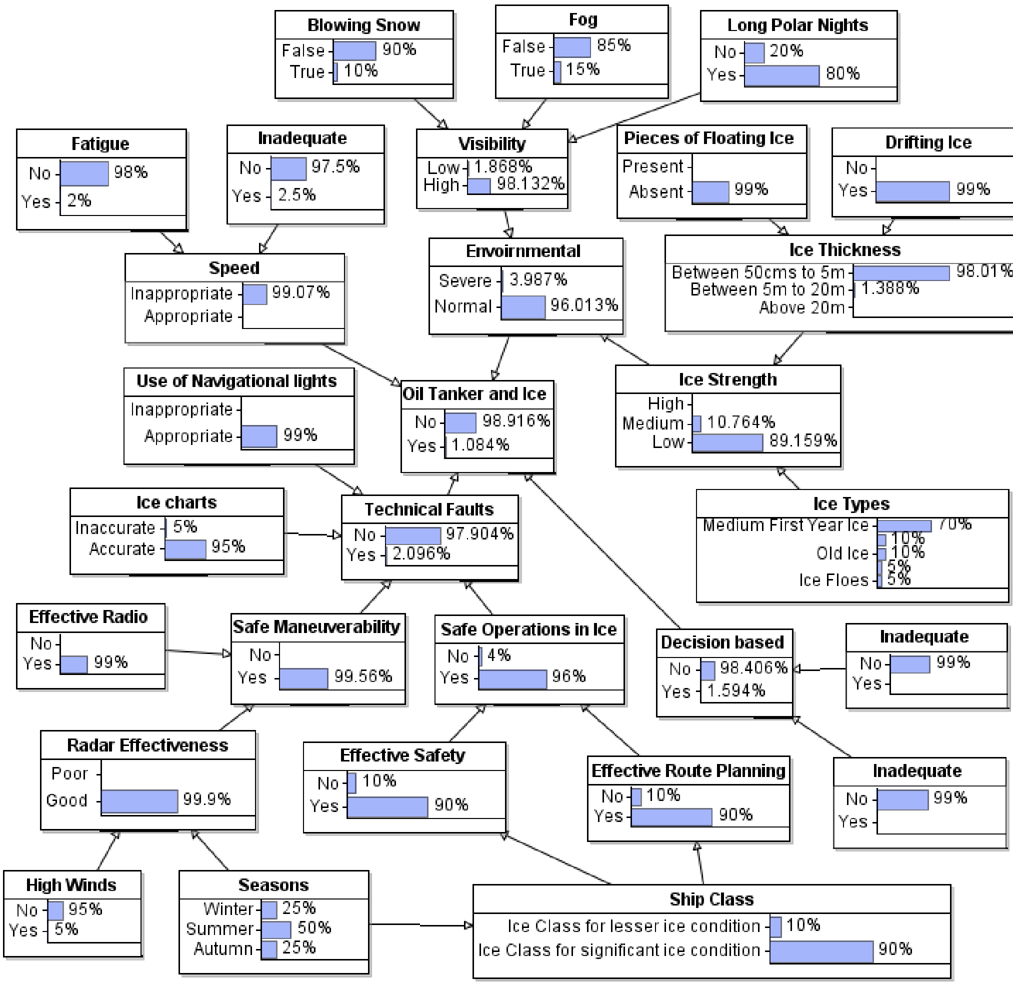

Figure 2.17. Risk of Oil Tanker-Ice Collision (using standard BN)

Table 2.3. Sensitivity analysis for the risk factors in OOBN of Figure 2.10 when Ship Navigational System States in NSR are inadequate

Ranking	Risk Factors	Sensitive value
1	Safe Maneuverability in Ice Covered Waters	0.318
2	Use of navigational lights and Search lights	0.317
3	Ice Charts	0.256
4	Effective Radio Communication	0.105
5	Radar Effectiveness	0.105

Table 2.4. Sensitivity analysis for the risk factors in OOBN of Figure 2.11 when Ship Operational System States in NSR is poor

Ranking	Risk Factors	Sensitive value
1	Safe Operations in Ice	0.310
2	Speed	0.301
3	Effective Safety Measures	0.121
4	Effective Route Planning	0.068
5	Ship Class	0.036
6	Seasons	0.031

Table 2.5. Sensitivity analysis for the risk factors in OOBN of Figure 2.12 when Weather System States in NSR are rough

Ranking	Risk Factors	Sensitive value
1	High Winds	0.476
2	Visibility	0.130
3	Fog	0.060
4	Blowing Snow	0.053
5	Season	0.050
6	Long Polar Nights	0.049

Table 2.6. Sensitivity analysis for the risk factors in OOBN of Figure 2.13 when Ice States in NSR is high

Ranking	Risk Factors	Sensitive value
1	Ice Strength	0.204
2	Ice Thickness	0.204
3	Pieces of Floating Ice/Icebergs	0.072
4	Drifting Ice	0.051
5	Ice Types	0.011

Collision in NSR, while *Technical Faults* result from the inadequacy of *Ship Navigational System States* and the poor *Ship Operational System States,* respectively. Table 2.8 shows that the severe "*Environmental Conditions"* is further responsible for the *Collision*, whereas, the high *Ice States* and the rough *Weather States* in NSR contribute to the severe *Environmental Conditions* in the region.

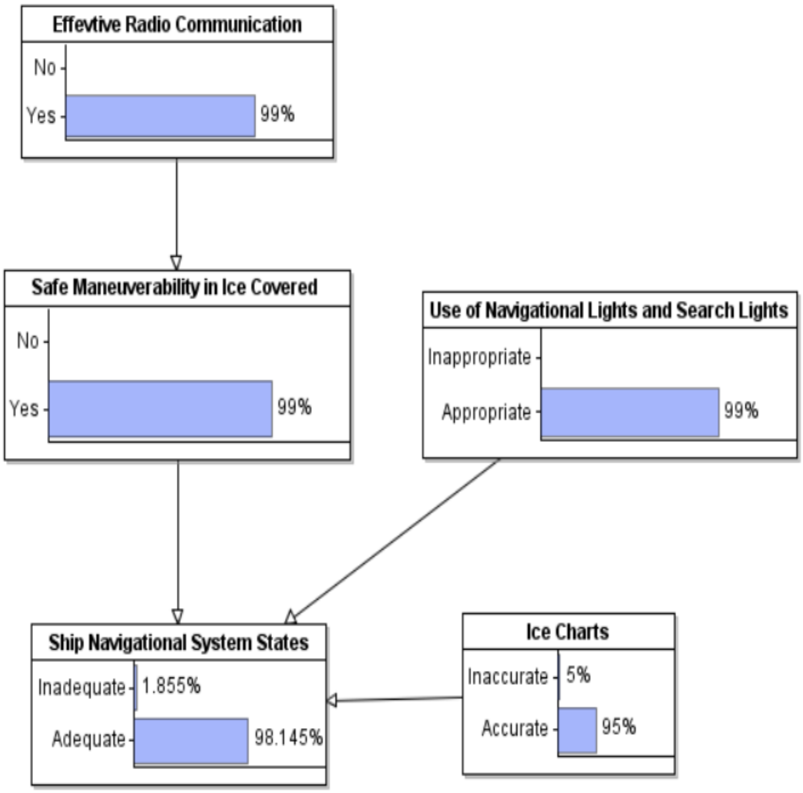

Figure 2.18. Removal of the Radar Effectiveness node from the Ship Navigational System States.

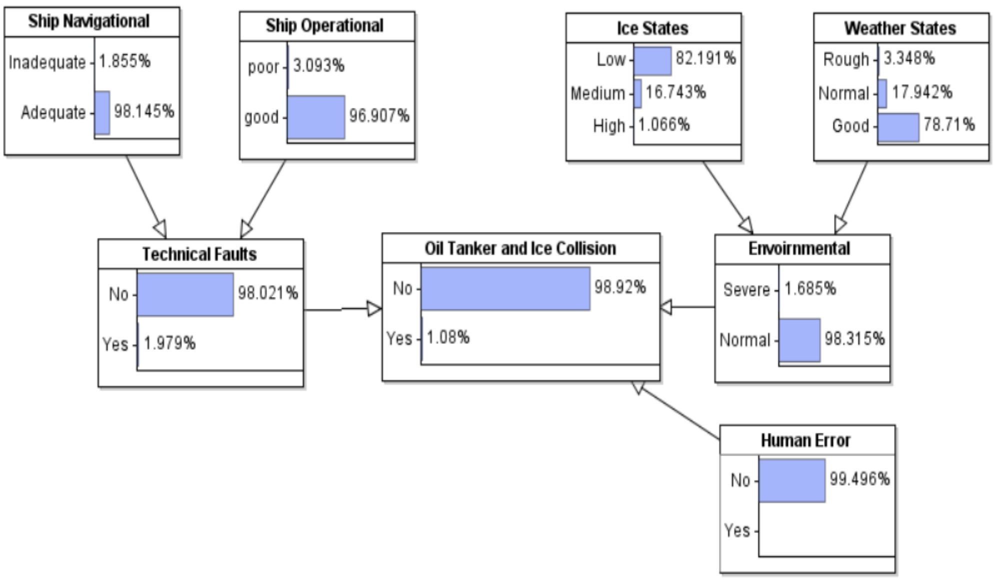

Figure 2.19. The collision model update after deleting the node Radar Effectiveness.

Table 2.7. Sensitivity analysis for the risk factors in OOBN of Figure 2.14 when the possible Human Error during the journey in NSR is affirmative.

Ranking	Risk Factors	Sensitive value
1	Decision based on Inadequate Information	0.118
2	Inadequate Communication	0.110
3	Fatigue	0.110
4	Inadequate Knowledge of own Ship System	0.029
5	Inadequate Technical Knowledge	0.029

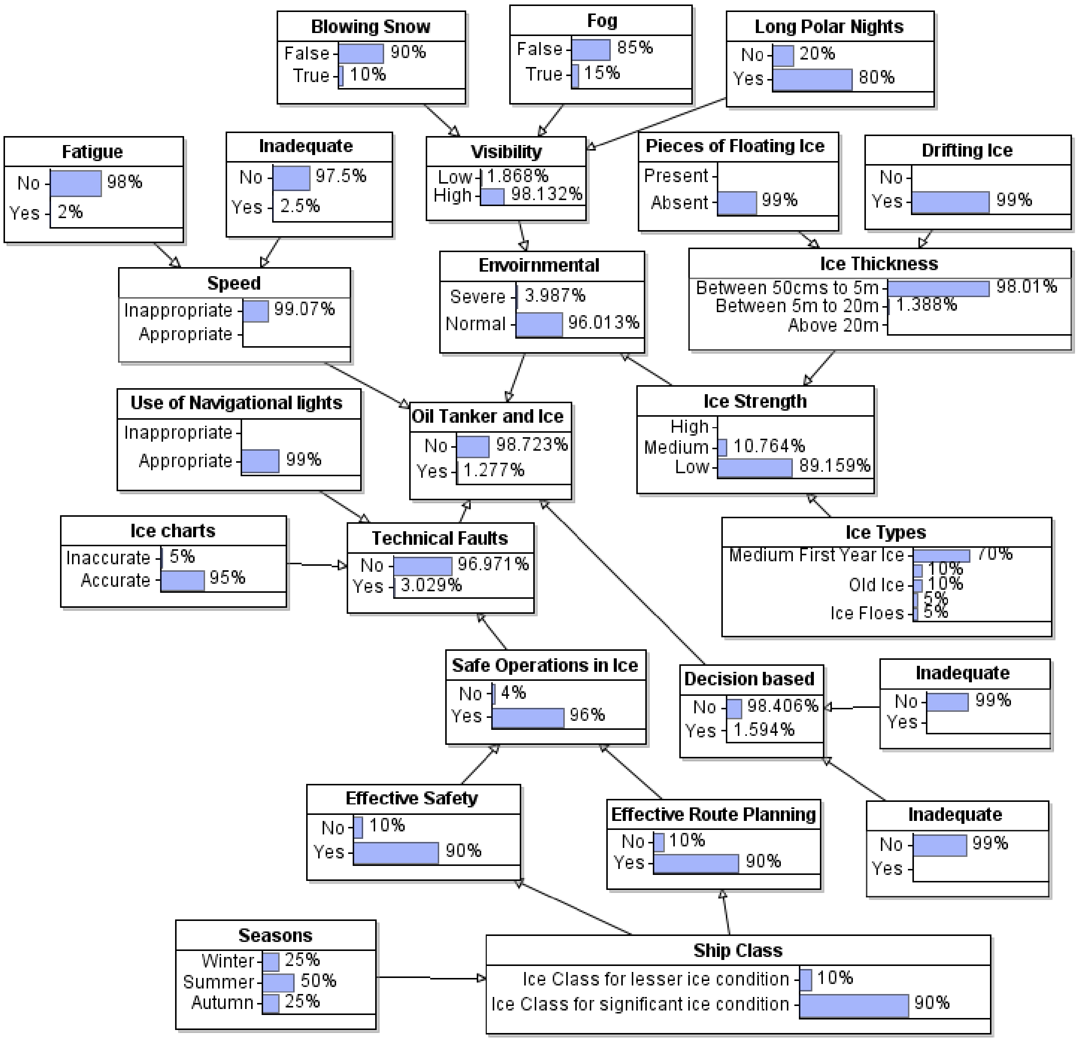

Figure 2.20. Collision Model after deleting the node Radar Effectiveness.

Table 2.8. Sensitivity analysis for the risk factors involved in the Oil Tanker-Ice Collision in NSR.

Ranking	Risk Factors	Sensitive value
1	Human Error	0.311
2	Technical Faults	0.304
3	Environmental Conditions	0.205
4	Ship Navigational System States	0.128
5	Ship Operational System States	0.127
6	Weather States	0.087
7	Ice States	0.074

Table 2.9. Classification of uncertainty and sensitivity (adapted from (Flage & Aven, 2009)).

	Significant	Minor	Moderate
Degree of Uncertainty	One or more of the following conditions met: (a) The involved phenomenon is not well understood (b) The model assumptions (e.g. risk factors for proposed OOBN) made in the study requires strong simplifications (c) Data is not available or unreliable (d) There is a lack of agreement among experts	All of the following conditions are met: (a) The involved phenomenon is well understood (b) The model assumptions (e.g. risk factors for proposed OOBN) made in the study are very reasonable. (c) Much reliable data is available. (d) There is a broad agreement among experts	Conditions between significant and minor uncertainties: (a) The involved phenomenon is well understood, but the model used in the study is not well defined (b) Some reliable data is available
Degree of Sensitivity	Relatively very small changes are required in the model to alter the conclusion	Relatively very large changes are required in the model to alter the conclusion	Relatively large changes are required in the model to alter the conclusion.

The above analysis reveals that the OOBN methodology allows us to investigate the root cause of *Oil Tanker-Ice Collision* individually without affecting the other factors that are not directly related to the collision accident.

2.4.2.2. Uncertainty Analysis

Proper treatment of uncertainty is an essential part of QRA. In order to describe the complete picture of risk, it is required to consider both the possible consequences related to the activity or a system and their associated uncertainties (Flage & Aven, 2009). Uncertainties are defined in terms of (1) Aleatory uncertainty, and (2) Epistemic uncertainty. Uncertainty about the occurrence of events is referred to as aleatory uncertainty, while the uncertainty that is associated with the lack of background knowledge about the events is termed as the epistemic uncertainty. The epistemic uncertainties can be reduced, but aleatory cannot and is sometimes called the irreducible uncertainty (Helton & Burmaster, 1996). The present study analyzes the epistemic uncertainty of the risk factors involved in the proposed OOBN methodology to see how uncertainty affects the risk of collision. For this purpose, the semi-quantitative method presented by (Aven, 2008) and (Flage & Aven, 2009) is used here, which assesses the effect of uncertainty inherent with the risk factors used in the OOBN model on the risk of collision. Flage and Aven (2009) further say that the effects on risk depends on the *degree of uncertainty* and *sensitivity of the relevant risk to changes in uncertain quantities*. A combination of high degree of uncertainty with high sensitivity could have a significant effect on model output. Nonetheless, for the case when the degree of uncertainty is high, and the model is insensitive to changes it is reasonable to consider a moderate or minor effect on risk. The classifications of uncertainty and sensitivity are shown in Table 2.9.

According to the above classification, if the model assumptions are highly uncertain, but are reasonable, and the model itself is insensitive to changes and well defined, then the effect on risk is minor or moderate. In the present study, some important model assumptions, *"Ice Strength",* and *"Decision based on Inadequate Information",* are relatively highly uncertain because of the arbitrary data is given to their priors – the parent nodes (see Figures 2.10 to 2.14). These assumptions have been collected from various sources (see Section 2.3 for the detailed explanation).

The model (OOBN) is well defined as it is used to reduce the complexities occurred in standard BN and it is moderately insensitive to changes. For instance, the effect of altered values of the risk factors such as *"Safe Maneuverability in Ice Covered Waters", "Safe Operations in Ice", "Visibility", "Ice Strength",* and *"Decision based on Inadequate Information",* on model outputs is clearly seen from Figures 2.21-2.25. However, due to the unavailability of data, we assume that the effect of uncertainties on modeled risk should be moderate (see Figure 2.26; compare the values of outputs in Figures 2.10-2.15 with 2.21-2.26). Table 2.10 summarizes the effects of the uncertain risk factors on the model output. The remaining risk factors considered in the model can be assessed by using the same analysis.

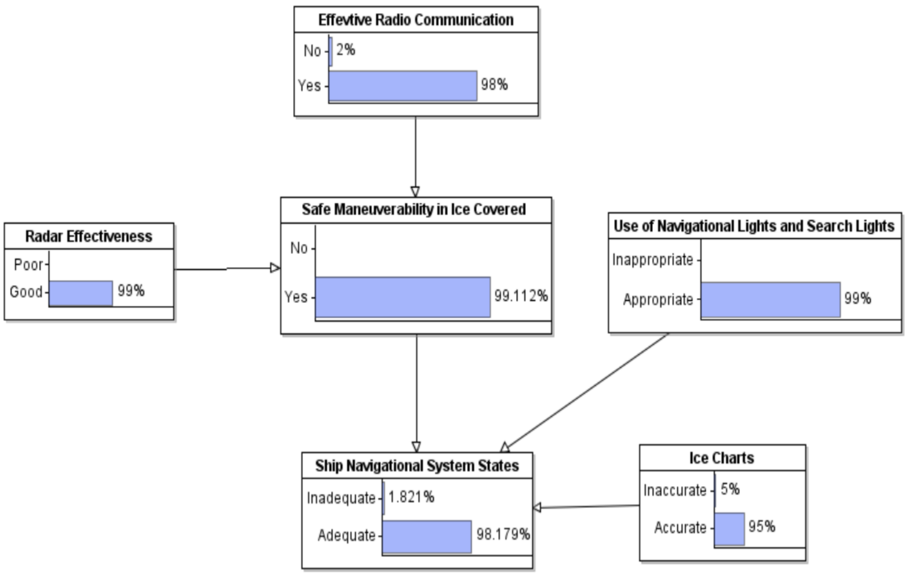

Figure 2.21. Effect of the altered value of *"Safe Maneuverability in Ice Covered Waters"* on the output *"Inadequate Ship Navigational States"*.

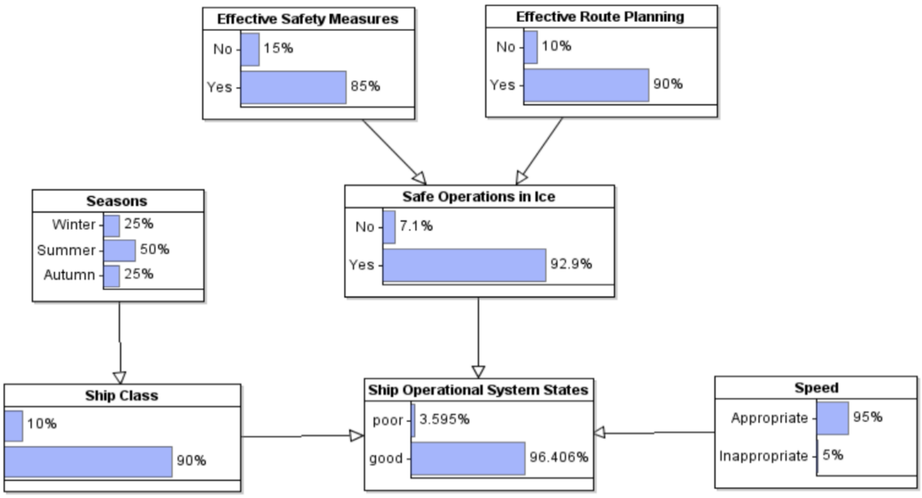

Figure 2.22. Effect of the altered value of *"Safe Operations in Ice"* on the output *"Poor Ship Operational System States"*.

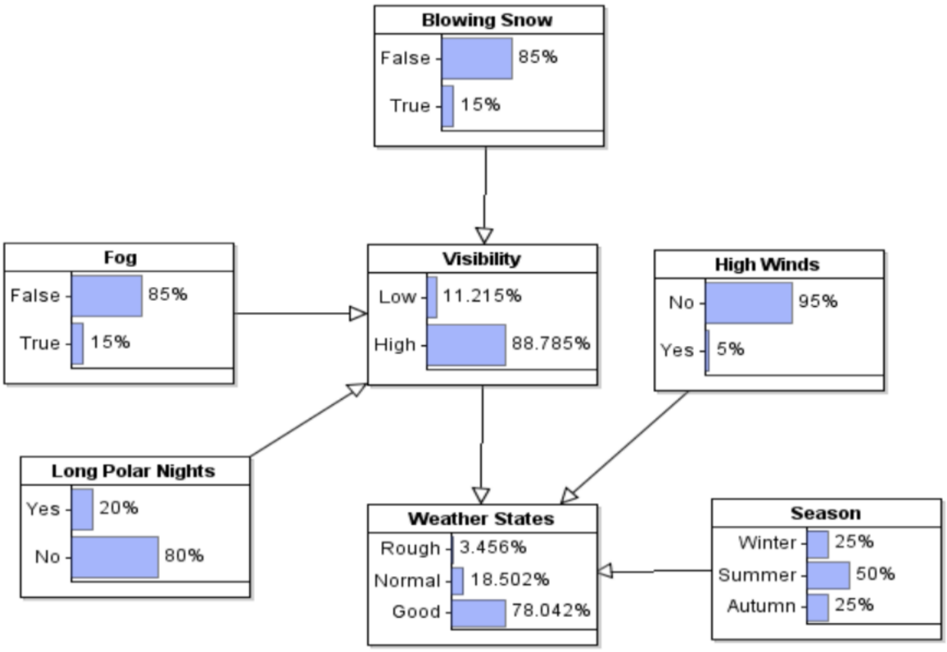

Figure 2.23. Effect of the altered value of "*Low Visibility*" on the output *"Rough Weather System States"*.

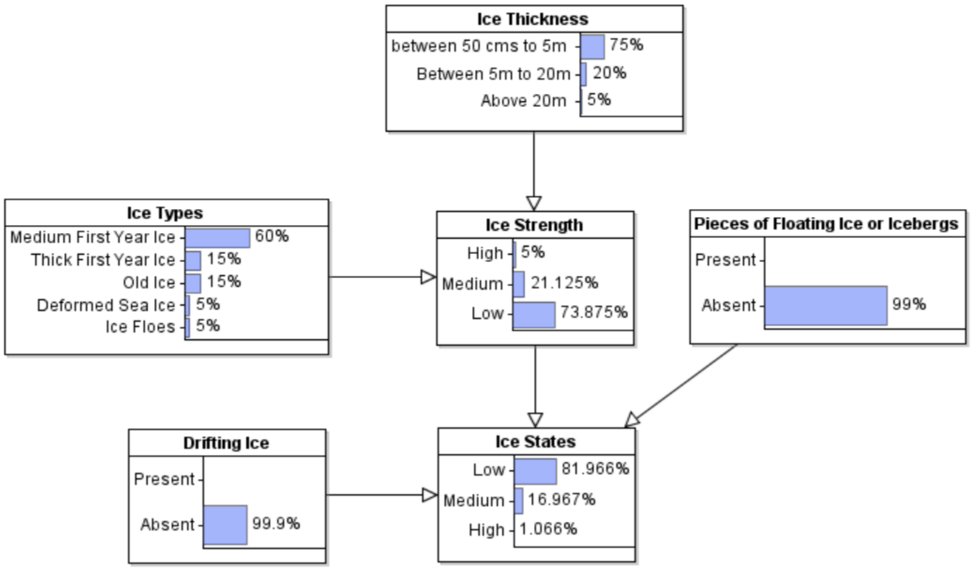

Figure 2.24. Effect of the altered value of *"Ice Strength"* on the output *"High Ice States"*.

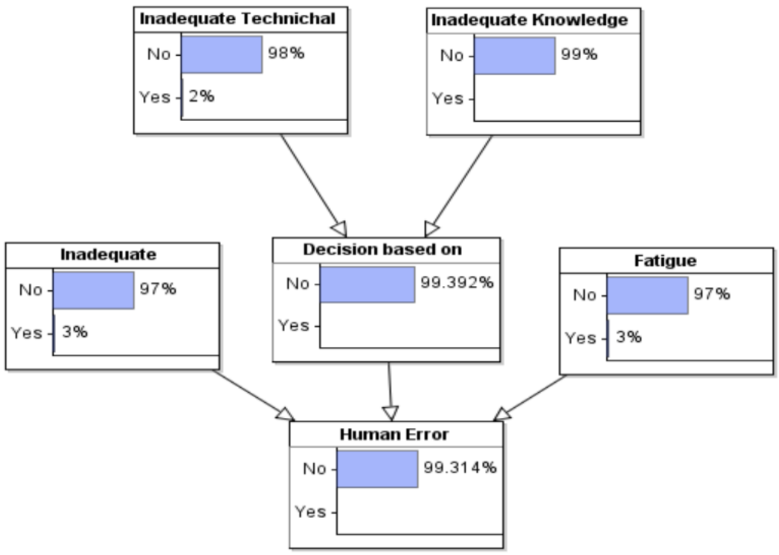

Figure 2.25. Effect of the altered value of *"Decision based on Inadequate Information"* on the output *"positive Human Error"*.

Table 2.10. Effect of uncertainties of risk factors/model assumptions on the risk of collision.

Risk factors	Minor	Moderate	Significant
Safe Maneuverability in Ice Covered waters		x	
Safe Operations in Ice		x	
Visibility		x	
Ice strength		x	
Decision based on Inadequate Information		x	

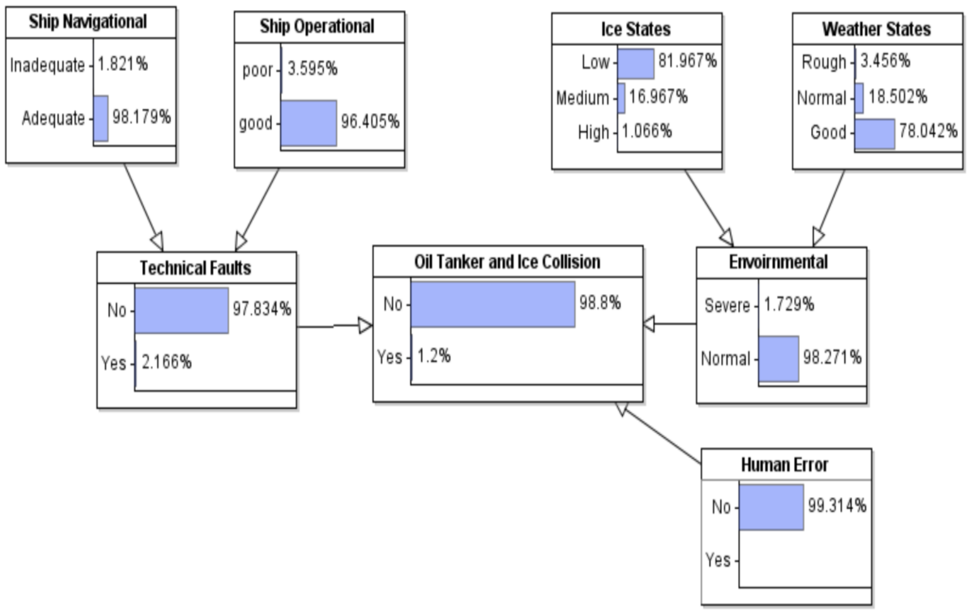

Figure 2.26. Effect of the altered values on *Risk of Collision.*

2.5 Conclusions and Future Directions

A model based on OOBN methodology is proposed and implemented to analyze the risk of maritime transportation in Arctic waters. The applicability of the proposed model has been demonstrated through a case study of risk analysis of Oil-Tanker-ice collision in ice-infested waters. The analysis reveals that,

- Human error has the greatest impact on oil-tanker ice collision in NSR.
- Technical faults results from the inadequacy of ship navigational system state and the poor ship operational system states are next to human error that contribute in collision, and
- Severe environmental conditions further responsible for the collision in NSR.

In the present study, on the basis of identified risk factors, the OOBN model is proposed to develop the risk based scenario of ship-ice collision in the Arctic waters to assess the risk of collision in the region. The proposed model simplifies the complicated marine accident modelling through hierarchical and component-by-component analysis, it identifies the root causes of an accident and analyze them individually, it can also expand without affecting its existing components to realize new functions in future. The uncertainty analysis in the study also reveals that the proposed OOBN framework is insensitive to changes but due to the unavailability of the data, we assume that the effect of uncertainties on modeled collision risk is moderate. In the present study, the validity of the proposed OOBN model has checked on the route from Murmansk to China that includes the Kara Sea, the Laptive Sea, and the East Siberian Sea. However, with the little modification in the changing sea-ice and weather related conditions, the model can be applied to the other routes of the Arctic waters, for instance, the routes of Barents Sea, the Vilkitskii strait, and the routes of ice-infested waters of Atlantic Ocean, for instance, the St. Lawrence Seaway.

The probability obtained through the proposed method can be used to support vessel operations decisions, such as navigational route selection and adjustment. Future research work is needed to expand this model and integrate it with decision-theoretic troubleshooting for vessel operation control to minimize navigational and operational risk in Arctic waters. For instance, a decision support system on corrective action selection and optimization for vessel operation can be investigated.

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Chapter 3

A Dynamic Bayesian Network model for ship-ice-collision risk in the Arctic waters[†]

Co-authorship statement. A version of this chapter is under peer review in the journal titled *Safety Science published by Elsvier*. The lead author, Bushra Khan, has developed the model, tested the model, analyzed its results and wrote the manuscript. Co-authors Dr. Faisal Khan and Dr. Brian Veitch have supervised this study. They have made technical contributions by providing the conceptual understanding of the model and subsequently provided technical feedback, reviewed the model and results. All authors read and approved the final draft.

Abstract. Extreme weather conditions of the Arctic and its icy waters pose high-risk potential for a range of marine accidents in the region. Ship-ice collision is the focus of this paper. A large number of vessels operating in the Arctic waters are at risk of ice damage due to ship-ice collisions. The damage may vary from a minor hull deformation to ruptures that could put the lives, assets, and environment at risk. To minimize the risk of ship-ice collision in Arctic waters, a simple yet robust model to make routine safety-driven operational decisions could help. The present study proposes a Dynamic Bayesian Network (DBN) model to fill this gap. The model assesses the operational risk of ship-ice collision in an ice prone region using the hypothetical form of observations. *Low temperatures, Weather, Ice, Fog, Darkness, Blowing snow, Poor visibility, Ice strength, Ice drift, Types of ice, Ice concentration* and *Speed of the vessel* are considered as the primary risk factors in the region. The estimated collision risk would provide an easy to use indicator for decisions concerning safe operations in ice such as maneuvering, route selection, and safe speed. A case study of an oil tanker navigating across the *Barents Sea* is presented to explain the proposed model.

[†] Khan, B., Khan, F., & Veitch, B. (2020). A Dynamic Bayesian Network model for ship-ice-collision risk in the Arctic waters. Accepted to publish in *Safety Science*.

3.1 Introduction

Though maritime transportation entails risks to lives, environment, and assets, it is a significant enabler of the development of natural resources and international trade. The safety of ships at sea is one of the main concerns of ship designers, shipbuilders, and ship owners (Soares & Teixeira, 2001). For ensuring safety at sea, that is, preventing human injury or loss of life and avoiding damage to the environment and loss of assets, the International Maritime Organization (IMO) has introduced the International Safety Management Code (ISM Code) (IMO, 1993). The ISM Code recognizes the need to ensure shipping companies take responsibility for managing the safety of their ships. While the International Convention for the Safety of Life at Sea (SOLAS) is an additional important regulation to make the shipping safer and reliable.

The Arctic has attracted attention due to its short shipping routes and large oil resources. Compared to the Suez and Panama canals, the Arctic Ocean is the shortest transit route between the northern ports of the Pacific and the Atlantic (Østreng et al., 2013). Arctic waters are known for their harsh weather and icy waters. Over the last few decades, a strong warming trend in the region has caused a significant reduction in sea ice cover (Østreng et al., 2013). This reduction benefits some of the marine activities in the region, but the challenging weather of the region could render the activity dangerous. To reduce such risk, the International Maritime Organization (IMO) has implemented the International Code for Ships Operating in Polar Waters (Polar Code), which came into force in 2017. It deals with the risks associated with design, construction and equipment, operational and training issues, search and rescue, and the environmental protection of Polar waters and their related ecosystems (IMO, 2017).

In recent years, various studies have also been proposed to reduce the risks in the region, for example, Kum and Sahin (2015) investigated some causes of ship accidents in the region from 1993 to 2011 through root cause analysis. The authors proposed recommendations to reduce the occurrence probabilities of accidents, such as collisions and groundings in the Arctic by applying the Fuzzy Fault Tree (FFT) analysis. They concluded that safety is a real problem in the Arctic region and suggested that more Arctic navigation training centers are needed. Smith et al. (2015) observed in their study that the sinking and grounding of fishing vessels from 1995 to 2004 were the most common accidents in the Arctic. The authors presented a comprehensive accident model that describes Arctic shipping accidents and their causation factors. The model identifies four factors that can influence Arctic shipping accidents: external, organizational, direct, and operational. They also identified three types of consequences: near misses, incidents, and accidents. The model also identifies that the ability to intervene is an important element to reduce the occurrence of an accident and its severity. They used case studies of the Kolskaya and Kulluk accidents to explain their model.

Fu et al. (2016) considered hydro-meteorological parameters, such as wind speed, air temperature, visibility, sea temperature, ice concentration, ice thickness, wave height, and ship performance parameters, such as ship speed, and engine power as risk influencing factors for Arctic navigation. By taking aforesaid influencing parameters as an input, the authors applied a Bayesian Belief Network to predict the probability of ship besetting in ice along the analyzed route. The results of the study strongly suggested that prior judgments of safety and sailing conditions are necessary for ice-going ships before sailing in Arctic waters. Baksh et al. (2018) used BN to investigate the possibility of marine accidents, such as collision, foundering, and grounding along the Northern Sea Route (NSR). In the proposed risk model, the different operational and environmental factors are considered as the factors that affect shipping operations in the Northern Sea Route (NSR). The authors demonstrated the application of the model by taking a case study of an oil-tanker navigating the NSR. The case study indicated that collision, grounding, and foundering probabilities are high in the East Siberian Sea. The model suggested that ice conditions are a dominant factor in accident causation in the NSR. Aristova and Gudmestad (2014) reviewed the loss of the Kolskaya jack-up platform in the Sea of Okhotsk in 2011. The authors also reviewed the near-disaster of the Kulluk rig, when the rig was being towed from Alaska to the US in January 2013. Both incidents occurred during towing in harsh weather, thus the authors suggested thorough risk analysis prior to critical tow operations. They also highlighted the responsibility of the marine staff who are involved in such types of operations and emphasized the need to strengthen their role during towing operations in harsh weather.

F. Khan et al. (2014) proposed a cause-consequence based model using BN to assess the transportation risk in Arctic waters. They estimated the probability of maritime accidents in the Arctic and their related consequences. Kum and Sahin (2015) discussed various risk factors for Arctic navigation, calculating the risk with probabilistic numerical levels by using the Fuzzy-AHP approach. Goerlandt et al.

(2017) present an analysis of navigational shipping accidents in the Northern Baltic Sea area that are occurred during the period of 2007-2013. The analysis is based on the integration of various data sources that aims to reconstruct the accident conditions on the best available data sources. Valdez et al. (2015) used accident data and expert judgments to assess the risk of winter navigation in Finnish sea areas. Marchenko et al. (2015) assessed the frequencies and consequences of collision (with sea ice/others objects), grounding, fire, violence, or terror for several cruise ships, cargo, tankers, petroleum installations, and fishing boats in the Norwegian and west Russian Arctic regions by using risk matrices. Afenyo, Khan, Veitch, and Yang (2017) analyzed Arctic shipping accident scenarios by using BNs. B. Khan, Khan, Veitch, and Yang (2018) considered several factors that influence the risk of Arctic navigation: ship navigational system states, ship operational system states, weather states, ice states, and human error. Based on those states, the authors proposed an OOBN model that predicts ship-ice collision probability in the Arctic. The authors explained the application of the model by presenting a case study of an oil-tanker navigating the NSR. The case study concluded that human error followed by the technical faults and severe environmental conditions have the greatest impact on oil-tanker collision in the region.

According to the statistics, collision, contact, and grounding are the most prominent shipping accidents (Kujala et al., 2009). Such accidents are mostly of a low probability-high consequence in nature (Elliott et al., 2008). In recent years, various studies have observed that BNs have potential to reduce the risks of marine accidents and the risks of their related consequences (Baksh et al., 2018; Fu et al., 2016;

Hänninen et al., 2014; Hänninen & Kujala, 2009; Khakzad et al., 2013; B. Khan et al., 2018; F. Khan et al., 2014; Montewka et al., 2014; G. Zhang & Thai, 2016).

G. Zhang and Thai (2016) discussed some of the basic reasons to choose BNs for modeling maritime accidents: a clear presentation of causal relationships, making both forward and backward inferences, combination of both experts' judgments and experimental data, its power to deal with uncertainty, and making updates with new information and observations. However, the difficulty in collecting experts' opinion is a common challenge that researchers have faced while using BNs for modeling maritime accidents.

BNs are especially preferred for their ability to model human and organizational factors, their ability to model common causes of accidents (Khakzad et al., 2013), and their ability to evaluate the risk control options (Mazaheri et al., 2014) and the mitigants to reduce the consequences. The application of BNs has also been proposed to the IMO for the third step of Formal Safety Assessment (FSA), which is the risk control options (Hänninen & Kujala, 2009). Valdez et al. (2016) also proposed a BN model to assess and manage the risk of winter navigation operations. The authors analyzed the risk of oil spills in winter navigation in the Gulf of Finland through the proposed model. Montewka et al. (2015) used Bayesian learning techniques to propose two probabilistic models evaluating ship performance in ice.

3.1.1 Limitations to BN

Even though BN is recognized as a vigorous approach to model marine accidents and useful to model expert opinions, it still has some limitations that need to be handled carefully, for instance; (1) Sometimes it is asked to the experts to provide both the model structure and probability distributions and sometimes only probability distributions are required. But if the phenomenon/process is complex or not well understood then the obtained model structure may be far away from a clear visualization i.e. inability to distinguish between causes and consequences in the model. While experts cannot be expected to produce appropriate probability distribution either. (2) In BNs it is also difficult to combine conflicting expert opinions. (3) Moreover, converting expert knowledge into the probability distributions is also a challenging task while using BNs (Uusitalo, 2007). (4) In BNs, reliable prior beliefs are also necessary to get reliable results. A minor mistake about the prior knowledge can distort the entire network and invalidate the results. (5) Since BNs are acyclic graphs, and thus do not support feedback loops (Jensen, 2001).

3.1.2 Quantitative Risk Assessment: A brief overview

Quantitative risk assessment (QRA) is also referred to as a probabilistic risk assessment (PRA). It systematizes the present state of knowledge including uncertainties about the process, activities, phenomena, and systems. It subsequently identifies possible hazards and threats in it along with their causes and consequences and describes the risk (Bai & Bai, 2014). Paltrinieri, Massaiu, & Matteini (2016) also define QRA as a combined approach to evaluate the risk level of an industrial system, which is typically based on the main technical failures that lead towards the potential accident scenarios. Montewka et al. (2014) stated a well-defined definition of risk in their study is " risk is a condition under which it is possible to define both a comprehensive set of all possible outcomes and to resolve a discrete set of probabilities across this array of outcomes" In QRA, risk is described in terms of probabilities and expected values. Flage & Aven (2009) explain in their study that QRA is an effective tool to capture a broad picture of risks of accidents as follows;

(a) In QRAs risk is usually described in terms of probabilities and expected values of hazards, and
(b) It has the ability to treat uncertainties related to the risk obtained for the desired event.

Aven (2012) and Goerlandt & Montewka (2015) also explain that in QRAs, the risk has been defined as expected value, probability of an undesired event, uncertainty, potential losses, probability and severity of consequences, event or consequences, consequences + uncertainties, and effect on uncertainty on objectives.

Most of the models in QRA utilize the concept of fault trees (FT) and event trees (ET) in the field of the maritime transportation system (MTS), which in certain cases may not completely show reality as they only allow one-way inference. This one-way inference may limit the applicability of FTs and ETs in the field of systematic risk mitigation and management (Montewka et al., 2014). This limitation has been recognized in QRA and various researchers use BN in order to develop a proactive and systematic framework to assess the risk for MTS (Afenyo et al., 2017; Baksh, Al-Amin, Abbassi Rouzbeh, Garaniya Vikram, 2018; B. Khan et al., 2018; Khakzad et al., 2013; F. Khan et al., 2014). The present study also proposes a BN methodology as a probabilistic tool to explain the risk of ship-ice collision and applies uncertainty analysis to explain the uncertainties in the proposed model and also determines its effect on the obtained risk.

3.1.3 Structure of the paper

Though BN is identified as a reliable and robust tool to model marine accidents, it does not account for the time dependence or the interdependency of variables. In the present study, we have developed a risk based scenario of ship-ice collision on the basis of identified risk factors. Whereas, the risk factors are based on rapidly changing ice and weather conditions in the Arctic. In order to overcome the time independence limitation of the BN, we have used a DBN framework to model the scenerio of ship-ice collision risk for the Arctice waters. This work proposes a simple yet robust model for safety-focused operational decision making. The proposed model relies on the hypothetical form of data to assess the risk of collision in given operational conditions. The effectiveness of the proposed model is demonstrated using a case study for the winter navigation of oil-tanker on the Barents Sea. Before presenting details of the model, a brief description of DBN is given below (section 3.2). Section 3.3 presents the proposed BN model of the ship-ice collision, section 3.4 presents the associated DBN model of the BN model, proposed in section 3.3 through a case study that uses a hypothetical accident scenario related to oil-tanker collision along the Barents Sea. Section 3.5 presents results and discussions. Section 3.6 discusses the conclusion of the study.

3.2 Dynamic Bayesian Network

DBN is a particular form of BN. DBN models the dynamics of the system by considering time dependence (Sarshar et al., 2013). The process is recursive and each time slice/timestep of the process acquires the same structural form as the previous or next slice (Fenton & Neil, 2013). Time slices reflect the change in the state/probabilities of the parameters in the model, this is the reason, the model is called dynamic. The state of a system at time t in a DBN is represented as follows, where, $X_1, X_2, \ldots, X_n$ are the set of random variables. The general structure of DBN is shown in Figure 3.1. The previous, current, and future time slices are represented as t−1, t, and t+1 respectively. The relationship between the variables within a time slice is called intra slice arcs, and the relationship between the variables in different time

$$X_t = X_{t_1}, X_{t_2}, \ldots, X_{t_n} \tag{3.1}$$

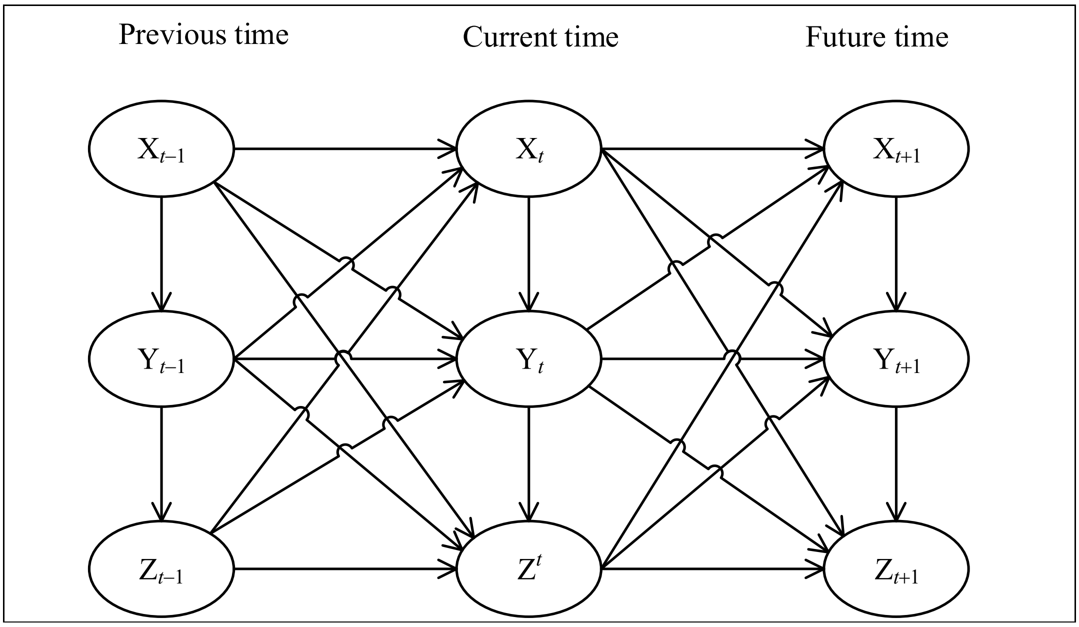

Figure 3.1. General structure of DBN.

slices is called inter time slices (Cai et al., 2013). $X_{t-1}, Y_{t-1}, Z_{t-1}$, X_t, Y_t, Z_t, X_{t+1}, Y_{t+1}, and Z_{t+1} are the sets of random variables in previous, current, and future time slices respectively. The Hidden Markov model is considered as the simplest DBN (Onisko, 2010). DBN supports multivariate time series i.e. not limited to a single time series. It supports both temporal and non-temporal nodes in the same model. Whereas, temporal nodes are the initial conditions observed at time t = 0. DBNs are the probabilistic graphical models that are used to describe the uncertainties of diverse situations. They can reduce the computational complexities, predict complex phenomena, and provide support to decision making in the scenarios where data is not clear and variables are highly interlinked (Sarshar et al., 2013). Cai et al. (2013) used DBNs to assess the risk of human factors on offshore blowout and Sarshar et al. (2013) used DBNs to model passengers' panic during a ship fire.

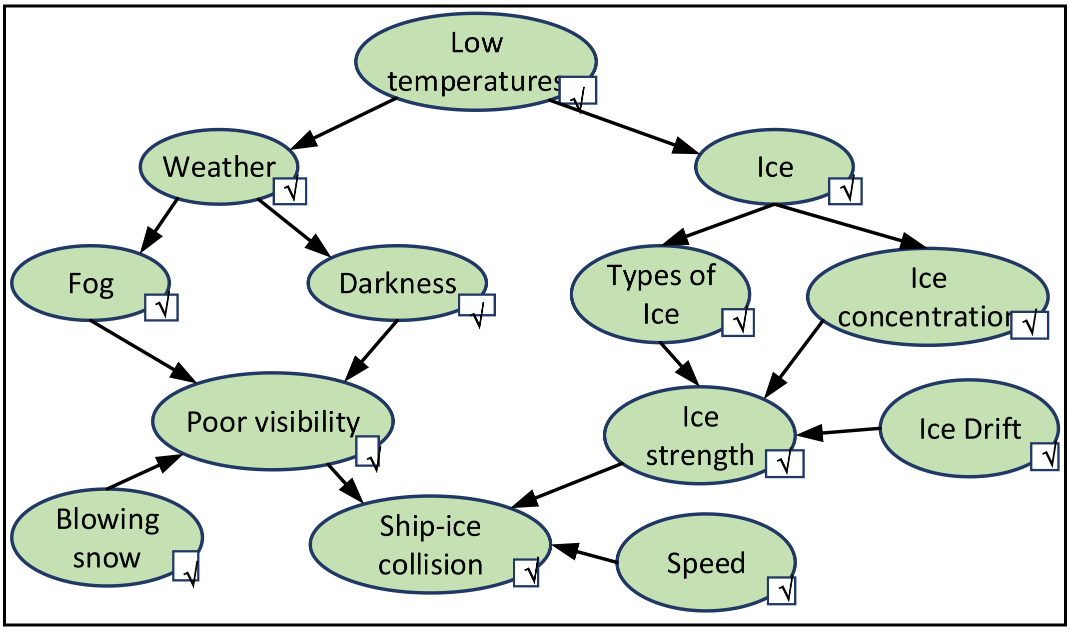

Figure 3.2. Ship-ice collision model for the winter navigation in Arctic waters

3.3 The Proposed Methodology

Figure 3.2 shows the proposed methodology of the ship-ice collision (*C*) model for the winter navigation of a vessel in the Arctic region. The model is simple and static in nature that aims to explain the primary risk factors of the ship- ice collision in the region and their dependencies without the influence of time.

3.3.1 Defining the risk factors used in the ship-ice collision model

The proposed BN model in Figure 3.2 is based on *Low temperatures* (*L*), *Weather* (*W*), *Ice* (*I*), *Fog* (*F*), *Darkness* (*D*), *Blowing snow* (*B*), *Poor visibility* (*P*), *Ice strength* (*IS*), *Ice drift* (*ID*), *Types of ice* (*T*), *Ice concentration* (*IC*) and *Speed of the vessel* (*S*). *L,* weather parameters *W* such as, *F* and *D* potentially increase the navigational risk at different locations of higher latitudes due to *P*. *B* in the region can also create unsafe working conditions for the personnel due to *P*. Such severe conditions may affect the performance of the equipment, material characteristics, and the functionality of the vessels, which, if not operated correctly, reduce the functionality and availability of the safety barriers (Galić et al., 2013). Such reductions in the safety barriers can cause the ship to collide with ice or another object. The presence of sea ice *I* in terms of high *IS* and *IC* along with the presence of *ID* at different locations are considered as the major threats to vessel operations in the region. Kubat and Timco (2003) found that most ships in the Canadian Arctic were damaged due to the presence of multiyear ice. Canadian Coast Guard (2012) and ABS advisory (2014) also recognized that the presence of various types of ice *T* such as thick first-year ice, old ice, ice floes, and deformed ice are significant risks for the Arctic navigation.

Marchenko (2012) reveals in his study that most of the casualties in the Russian Arctic occurred due to sea ice.

To reduce the navigational risks in the ice-covered waters, *S* is an important factor to be controlled. For such purpose, B. Khan, Khan, & Veitch (2019); B. Khan et al. (2018) and F. Khan et al. (2014) proposed models in their studies that can be able to manage the safe speed of ships in ice. Authors of the abovesaid studies consider (*S*) as an operational risk factor, however, in the present study, we associate the speed of a vessel with the environmental conditions of the Arctic.

3.3.2 Defining the structure of the ship-ice collision model

During the period in which the Arctic routes are accessible, vessels can expect to encounter low temperatures, causing ice formation and foggy weathers along with the darkness due to the long polar nights. We, therefore, take the *L* node as the parent node of *W* and *I* nodes and take *W* node as the parent node of *F* and *D* nodes in Figure 3.2. Since fog, darkness, and blowing snow are the main factors causing reduced or poor visibility, therefore, *F, D,* and *B* are taken as the parent nodes of *P* node in Figure 3.2. Likewise, *I* node in Figure 3.2 is taken as the parent node of *T* and *IC.* Since, types of ice (including shape and size), ice concentration, and drift ice account for ice strength; therefore, *T, IC* and *ID* nodes are taken as the parents of *IS* node. Since both poor visibility and ice strength can cause ship-ice collision *C* in the Arctic, therefore, we take *(P)* and *(IS)* as the parent nodes of *C.* High speed in ice is also an important factor that can cause ship-ice collision therefore, (*S*) is also included in the set of parents of *C* node. To understand the structure of the proposed ship-ice collision model for this study, interested readers should consult (ABS advisory, 2014; Canadian Coast Guard, 2012; B. Khan et al., 2018; F. Khan et al., 2014; B. Khan et al., 2019; Sahin & Kum, 2015; Kubat & Timco, 2003; Baksh et al., 2018).

3.4 Associated DBN model of ship-ice collision model — *Winter navigation of oil-tanker on the Barents Sea*

This section presents the associated DBN model of the ship-ice collision model proposed in Figure 3.2 of section 3. The arcs are made dynamic and nodes (risk factors) are made time-dependent. The model is applied to the winter navigation of the oil-tanker on the Barents Sea.

The Barents Sea, situated between northwestern Europe, Svalbard, Franz Josef Land, and Novaya Zemlya. Freezing in the region usually starts from late September and reaching up to its greatest extent during March or April. In winters, the prevailing ice type in the Barents Sea is the first year FY ice. Northern parts of the Barents Sea influence the ice drifts *ID*, which is used to exchange a large amount of sea ice between the Arctic Ocean and the Kara Sea (Alexandrov et al., 2004). Also, the northern part of the Barents Sea hosts some of the other characteristics of Arctic waters during winters such as cold temperatures, darkness, and polar lows (i.e. low temperatures throughout the winters). Currently, a large percentage of Arctic shipping activity involves transportation through the Barents Sea. In 2009, the volume of oil exported to the western market through the region was estimated to be around 15 million tons (Østreng et al., 2013).

The proposed model is used to calculate the risk of oil-tanker-ice collision, the time dependency of nodes and arcs in the model has to be altered according to the prevailing ice and weather conditions of the region. The model is intended to support operational decisions in connection with time, such as the selection of navigational routes, and safe speed to reduce the risks of C in the ice-covered waters. For instance, in the present study, it is assumed that oil-tanker is navigating on the Barents Sea, the hour-to-hour changings in sea-ice and weather related conditions in the region are continously observed during navigation. The changes are used to make updates in evidences, and based on the evidences, the hour-to-hour risks in the region are estimated. Tables 3.2, 3.3, and, 3.4 explain the process of updating evidences and calculating risks on hour-to-hour bases respectively. These hour-to-hour updates help

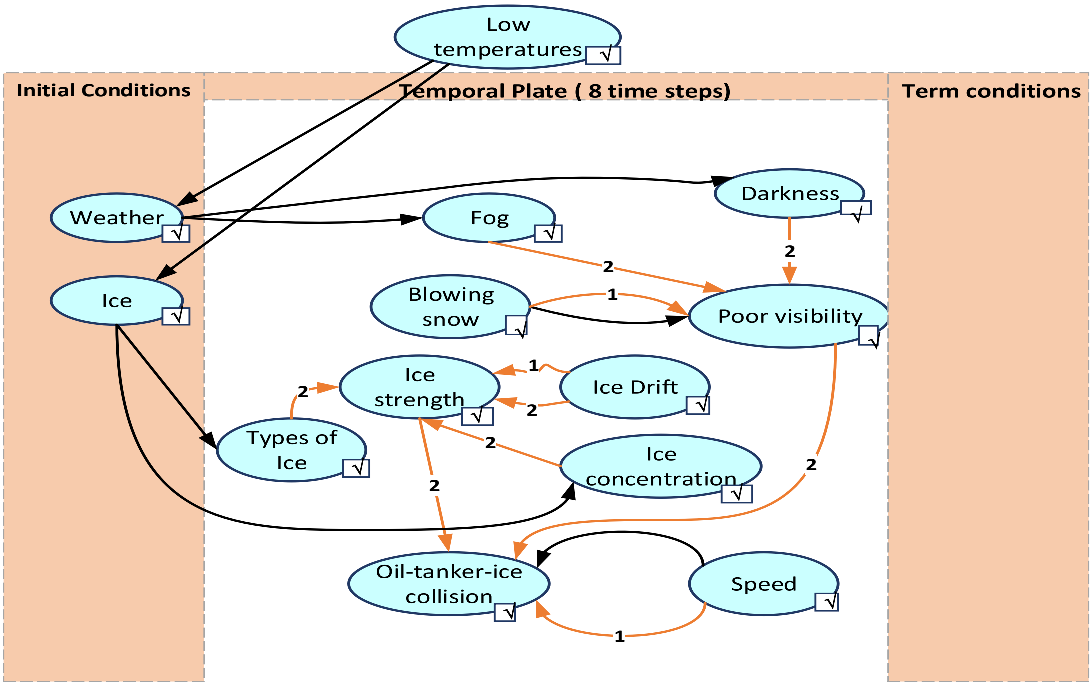

Figure 3.3. The DBN model of oil-tanker-ice collision for the Barents Sea (for winter navigation).

the oil-tanker to divert its path from challenging areas and reduce the risks of collision during navigation.

3.4.1 Temporal dependencies of the nodes in DBN: Working mechanism of the proposed DBN model

The present section discusses the temporal dependencies of the nodes in the proposed DBN model. The model in Figure 3.3 shows that the *Init Conditions (initial condition)* and *Term Conditions* are the parts of the network that consist of those nodes that have the children and parent nodes present inside the *Temporal Plate*. For instance, *W* and *I* are the *initial conditions* and the parent nodes in the model. Nodes existing outside the *Temporal Plate* are static. For instance, *Low temperatures* (*L*), in the model is taken as the static node because temperatures in winters are constantly low throughout the Barents Sea. Temporal nodes are based on temporal beliefs and evidence. Temporal nodes in the model are shown in the *Temporal Plate*; it is the area in DBN that shows the number of timesteps for which the Bayesian inference will be carried out, for instance, *F, D, B, P, IS, ID, T, IC*, *S,* and *C* are temporal nodes in the model (see Figure 3.3).

The dynamic arcs, that join the temporal nodes in the *Temporal Plate* represent changes over time among the variables (Figure 3.3). The single digits numbers on the arcs imply the temporal delay of influence (Onisko, 2010). For instance, an arc labeled as 1 between the variables *B* and *P* implies the influence that takes one timestep. An arc labeled as 2 between the variables *F* and *P* implies an influence that takes two timesteps. The model encodes the following conditional distribution over *C*:

$$P(C_t | IS_t, P_t, S_{t-2}, S_{t-1}) \quad (3.2)$$

Eq. 3.2 shows that conditional probability distribution for *C* at time = *t* depends on the current status of *IS* and *P* at time = *t*, also it depends on *S* recorded in one and two timesteps before at time = t–1 and t–2 respectively. In the proposed DBN model, we have arbitrarily selected 8 timesteps to perform the analysis, however, it can be extended for more timesteps. In order to record evidence, timesteps for the proposed DBN model can be chosen in terms of days, hours, or minutes. While, in the present study, timesteps have been selected in terms of hours and evidence has been recorded on an hour-to-hour basis, respectively. These timesteps are required to calculate the risk of collision for the entire journey.

3.4.1.1 CONDITIONAL PROBABILITY TABLES

There are three types of arcs coming into the node of oil-tanker-ice collision: (1) regular arc representing static relation between the nodes at timestep *t* = 0, (2) temporal arc with label 1at timestep *t* = 1, and (3) temporal arc with label 2 at timestep *t* = 2. This shows that there are three different conditional probability tables quantify oil-tanker-ice collision *C*. Eqs. 3.3-3.5 agree with the three conditional probability tables in the model as follows:

$$P(C_{t=0} | S_{t=0}) \quad (3.3)$$

$$P(C_{t=1} | S_{t=1}, S_{t=0}) \quad (3.4)$$

$$P(C_{t=2} | IS_{t=2}, P_{t=2}, S_{t=1}, S_{t=0}) \quad (3.5)$$

Table 3.1. Input values of *I, W, L* for the oil-tanker-ice collision model (for the winter navigation on the Barents Sea)

I	*W*	*L*
Presence	Harsh	*Temperature*
0.60	0.60	0.75

Eq. 3.3 shows that initially at timestep $t = 0$, *C* depends on the speed *S* of the oil tanker only. Eq. 3.4 shows that at timestep $t = 1$, *C* depends on the *S* which is recorded in previous timesteps i.e. at $t = 0$ and 1, respectively. Eq. 3.5 shows that at timestep $t = 2$, *C* depends on *IS*, *P,* and *S,* whereas, *IS* and *P* are recorded in current timestep i.e. at $t = 2$, and *S* is recorded in previous steps i.e. at timestep $t = 0$ and 1, respectively.

Similarly, the model (Figure 3.3) encodes the following distributions over *IS* and *P*:

$$P(IS_t|\, T_t, IC_t, ID_t, ID_{t-1}) \tag{3.6}$$

$$P(P_t|D_t, F_t, B_{t-1}, B_{t-2}) \tag{3.7}$$

Eq. 3.6 shows the conditional probability distributions over IS at time = t depends on the current status of T, IC, and ID at time = t, also it depends on ID recorded in one timestep before at time = t−1. Likewise, the conditional probability distribution over *P* at time = *t* in Eq. 3.7, depends on the current status of *D* and *F* at time = *t*, it also depends on *B* recorded in one and two timesteps before at time = *t*−1 and *t*−2 respectively. There are two types of arcs coming into the node *IS*: (1) temporal arc with label 1 at timestep $t = 1$, and (2) temporal arc with label 2 at timestep $t = 2$ and three types of arcs coming into the node *P*: (1) regular arc at timestep $t = 0$, (2) temporal arc with label 1 at timestep $t = 1$, and (3) temporal arc with label 2 at timestep $t = 2$. There are three types of conditional probability tables quantifying *IS* and *P* at timesteps $t = 0, 1, 2$ in the model. Eqs. 3.8-3.13 match the six conditional probability tables related to *IS* and *P* as follows:

$$P(IS_{t=0}) \tag{3.8}$$

$$P(IS_{t=1}|\ ID_{t=1}) \tag{3.9}$$

$$P(IS_{t=2}|\ T_{t=2}, IC_{t=2}, ID_{t=2}, ID_{t=1}) \tag{3.10}$$

$$P(P_{t=0}|B_{t=0}) \tag{3.11}$$

$$P(P_{t=1}|B_{t=0}, B_{t=1}) \tag{3.12}$$

$$P(P_{t=2}|D_{t=2}, F_{t=2}, B_{t=1}, B_{t=0}) \tag{3.13}$$

All nodes in the proposed model are Boolean except *IS* that takes values from the set {High, Moderate, Low}, and *T* that takes values from the set {MFI, TFI, OI, IF} respectively. Nodes *L, P,* and *C* take values from the set {Yes, No}, Nodes *ID, F, D, B* take values from the set {Present, Absent}. Nodes *IC* and *S* take values from the set {High, Low}, the node *W* takes values from the set {Harsh, Moderate}, and the node *I* takes values from the set {High, Moderate}. Input values (prior probabilities) of *I* (presence), *W* (harsh), and *L* are shown in Table 3.1.

The software GiNIie 2.2 (BayesFusion, 2018) is used to develop the proposed DBN model and perform computations for this study. Most of the data used in the model are for the illustrative purpose only.

3.4.1.2. Input data of *I*, *W*, and *L*

While, the input values (prior probabilities) (see Table 3.1) for the present study have been selected from the previous literature (Alexandrov et al., 2004; Østreng et al., 2013). Unlike the Kara and Laptev seas, sailing conditions in the Barents sea with respect to the ice and weather conditions are much favorable. In the winters, the ice area in the Barents sea usually comprises 55-60 percent of the total sea area.

Furthermore, freezing temperatures in the region reaching up to its greatest extent from March to April, covering 75 percent of the sea area with low temperatures (Østreng et al., 2013); Alexandrov et al., 2004). Thus, the input values of I (presence) and W (Harsh), and L (Temperature) nodes in Table 3.1 are considered into this prospect.

3.5 Results and Discussions

The DBN model presented in Figure 3.3 depends on the observations that are made at time = t, t–1, and t–2 respectively. The present section discusses the cases I, II, and III, that have been arisen from the proposed DBN model. Each case describes the risk-based scenarios for *C, IS,* and *P* separately. Equations that have been encoded through the proposed DBN model in Section 3.4 are used to calculate the risks of *C, IS,* and *P* individually. The present section also discusses the results that have been obtained through the said cases.

3.5.1 Case-I: Risk of Oil-tanker-ice collision (C)

In this case, the proposed DBN model will calculate the risk, (*R)* of oil-tanker- ice collision C (Eq. 3.14) with respect to the given dynamic evidence *IS, P,* and *S* at time = t, t–1, and t–2 as follows,

Table 3.2. Risk of collision C in the Barents Sea with respect to *IS, P,* and S at t, $t-1$, and $t-2$ respectively.

t in hours	Risk of Collision C	Dynamic evidence (input) for calculating C over time
0	0.10	Presence of low *IS*, high *P,* high *S* observed when the voyage is in its initial hour of the journey at $t = 0$.
1	0.25	Presence of moderate *IS* and high *P,* observed in current timestep $t = 1$; high *S* observed in timesteps t-1.
2	0.10	Moderate *IS* and high *P,* observed in current timestep $t = 2$ but low *S* is observed at t-1 i.e. at t=1 and high *S* is observed in t-2, i.e. at t=0 respectively.
3	0.10	Low *IS* and low *P,* are observed in current timestep $t = 3$, and high *S* is observed in t-1, i.e. at $t = 2$ and low *S* is observed in t-2 i.e. at $t = 1$ respectively.
4	0.25	Presence of high *P* and high *IS* are observed in current timestep t=4, and the constant high speed of a vessel is observed in t -1 and t -2 i.e. at $t = 3$ and t =2 respectively.
5	0.10	High *IS*, high *P* observed at current timestep $t = 5$; low *S* observed at t-1, and high *S* observed at t-2, i.e. at $t = 3$.
6	0.15	Low *IS,* no *P* are observed in current timestep $t = 6$, and constant low *S* is observed in t-1 and t-2 i.e. at $t = 5$ and $t = 4$ respectively.
7	0.15	Low *IS,* high *P* are observed in current timestep $t = 7$, and constant low *S* is observed in t-1 and t-2 i.e. at $t = 6$ and $t = 5$ respectively.

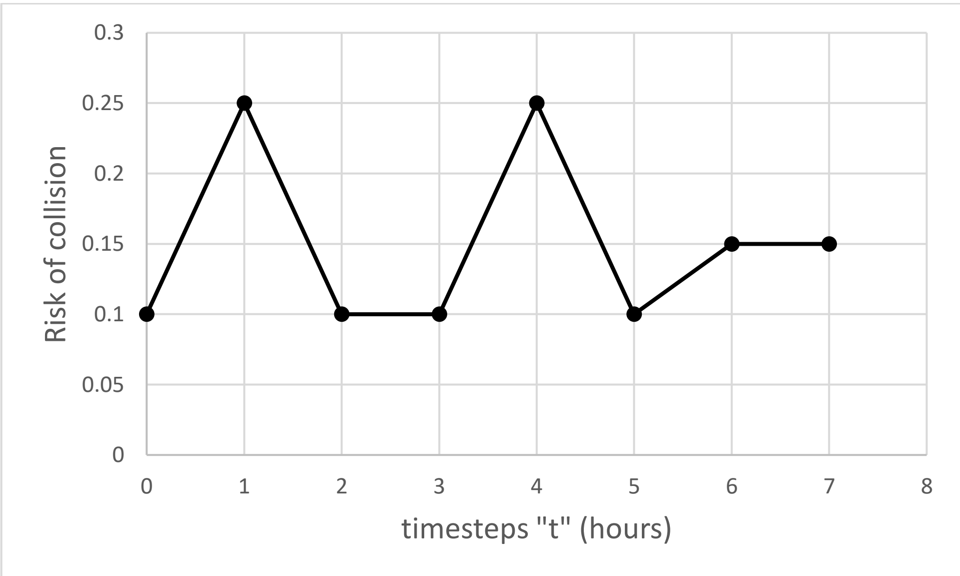

Figure 3.4. Risk of oil-tanker-ice collision C in the Barents Sea (hour-to-hour).

$$\text{Risk of } C = Prob(C(\texttt{yes})|E), \tag{3.14}$$

whereas,

$$E = IS_t(High), P_t\ (No), S_{t-2}\ (High), S_{t-1}(High) \tag{3.15}$$

whereas, Eq. 3.15. calculates evidence for C at time = t, $t-1$, and $t-2$ respectively, when the presence of high IS and absence of P are observed in current timestep t, and constant high S is observed in previous timesteps $t = t-1$ and $t-2$ respectively. Eq. 3.15 is continuously used to update evidence for C at time = t, $t-1$, and $t-2$ respectively.

3.5.2 Case-II: Risk of high Ice Strength (IS)

In this case, the proposed DBN model will calculate the Risk (R) of high IS with respect to the given sets of dynamic evidence such as T, IC, ID at time = t, $t-1$, and $t-2$ respectively, as follows:

$$Risk\ (R)\ of\ IS = Prob(IS(\texttt{High})|E), \tag{3.16}$$

where,

$$E = T_t(TFI), IC_t(\texttt{High}), ID_t(\texttt{present}), ID_{t-1}(\texttt{absent}) \tag{3.17}$$

Eq. 3.16 calculates R of IS with respect to T, IC, and ID at time = t, $t-1$, and $t-2$ respectively. Eq. 3.17 calculates evidence for high IS, at time = t, $t-1$, $t-2$ when the presence of Thick First Year Ice (TFI), high IC, and the presence of ID are observed in current timestep t, while, the absence of ID is observed at $t = t-1$ respectively.

Table 3.3. Risk of high *IS* in the Barents Sea with respect to *T, IC,* and *ID* at t, t-1, and t-2 respectively.

t in hours	R of high *IS*	Dynamic evidence (input) for estimating the probability of high *IS* over time
0	0.01	Presence of MFI, low *IC,* and absence of *ID* are observed in current timestep i.e. t =0, when the voyage is in its initial hour of journey.
1	0.20	Presence of MFI and low *IC* are observed in current timestep i.e. t =1 and the presence of *ID* is observed in current timestep i.e. t =1 and the absence of *ID* is observed in previous timestep t -1 i.e. t = 0.
2	0.50	Presence of high *IC* and OI are observed in current timestep i.e. t =2 and the presence of *ID* is observed in current timestep i.e. t =2 and in previous timestep t-1 i.e. t = 1 respectively.
3	0.15	Presence of MFI and low *IC* are observed in current timestep i.e. t = 3 and presence of *ID* is observed in current timestep t as well as in previous timestep t -1 i.e. t =3 and t = 2 respectively.
4	0.80	Presence of MFI and high *IC* are observed in current timestep i.e. t =4 and the presence of *ID* is observed in current timestep i.e. t =4 and in previous timestep t-1 i.e. t = 3 respectively.
5	0.50	Presence of high *IC* and OI are observed in current timestep i.e. t =5 and the presence of *ID* is observed in current timestep i.e. t =5 and in previous timestep t-1 i.e. t = 4 respectively
6	0.01	Presence of low *IC* and TFI are observed in current timestep i.e. t =6 and the absence of *ID* is observed in current timestep i.e. t = 6 and the presence of *ID* is observed in previous timestep t – 1i.e. t = 5 respectively.
7	0.15	Presence of low *IC* and IF are observed in current timestep i.e. t =7 and the absence of *ID* is observed in current timestep i.e. t = 7 as well as in previous timestep t – 1i.e. t = 6 respectively.

Eq. 3.17 is continuously updating evidence for Eq. 3.16 at time = t, t–1, and t–2, respectively.

3.5.3 Case III: Risk of Poor visibility (P)

In this case, the proposed DBN model will calculate the Risk *(R)* of *P* with respect to the given sets of dynamic evidence such as *D, F, B* at time = t, t–1, and t–2 respectively, as follows:

Table 3.4. Risk of *P* in the Barents Sea with respect to *D, F,* and *B* at *t*, *t*-1, and *t*-2 respectively.

t in hours	Probability of *P*	Dynamic evidence (input) for estimating the probability of *P* over time
0	0.99	Presence of *F* and absence of *D,* are observed in the current timestep i.e. *t* =0 when the voyage is in its initial hour of journey.
1	0.70	Presence of *F* and absence of *D,* are observed in current timestep i.e. *t* =1 and the presence of *B* is observed in previous timesteps *t* -1 i.e. at *t* =0.
2	0.70	Presence of *F* and absence of *D,* are observed in current timestep i.e. *t* =2 and the absence of *B* is observed in previous timestep *t* -1 i.e. at *t* =1 and presence of *B* is observed in previous step *t* – 2 i.e. *t* = 0.
3	0.30	Absence of *F* and *D,* are observed in current timestep i.e. *t* =3, and the continued absence of *B* is observed in both of previous timesteps *t* -1 and *t* -2 i.e. *t* =2 and *t* =1 respectively.
4	0.90	Presence of *F* and *D,* are observed in current timestep i.e. *t* =4 and the continuous absence of *B* is observed in both of previous timesteps *t* -1 and *t* -2 i.e. *t* =3 and *t* =2 respectively.
5	0.70	Presence of *F* and absence of *D,* are observed in current timestep i.e. *t* =5 and the presence of *B* is observed in previous timestep *t* -1 i.e. at *t* = 4 and the absence of *B* is observed in previous step *t* – 2 i.e. *t* = 3.
6	0.01	Absence of *F* and *D,* are observed in current timestep i.e. *t* =6, and the continued absence of *B* is observed in both of previous timesteps *t* -1 and *t* -2 i.e. *t* = 5 and *t* = 4 respectively.
7	0.70	Presence of *F* and *D,* are observed in current timestep i.e. *t* =7 and the continuous absence of *B* is observed in both of previous timesteps *t* -1 and *t* -2 i.e. *t* = 6 and *t* = 5 respectively

$$Risk\ (R)\ of\ P\ =\ P(P(Yes)|E) \tag{3.18}$$

where,

$$E = D_t(\texttt{present}), F_t(\texttt{present}), B_{t-1}(\texttt{absent}), B_{t-2}(\texttt{present}) \tag{3.19}$$

Eq. 3.18 calculates the *R* of *P* with respect to *D, F,* and *B* at time = *t*, *t*–1, and *t*–2 respectively. Eq. 3.19 calculates evidence for *P,* at time = *t*, *t*–1, *t*–2 when the presence of both D and F is observed in current timestep t, and the presence and absence of B are observed at $t = t{-}1$ and $t{-}2$ respectively. Eq. 3.19 is continuously updating evidence for Eq. 3.18 at time = t, $t{-}1$, and $t{-}2$, respectively.

3.5.4 Analyses of the results obtained through the risk-based scenarios presented in Cases I, II, and III

The analysis presented in Table 3.2 and Figure 3.4 indicates that the R of C at timestep t =1 is 0.25, which is beyond the assumed acceptable level of collision risk for winter navigation i.e. 0.15. However, this is due to the presence of moderate IS and P both are observed in current timestep t = 1 and high S of an oil-tanker is observed in previous timestep t = 0 — when the journey was in its initial hour, where the risk was observed to be 0.1. Similarly, the R of C in the region is also observed *0.25* at t = 4, due to the presence of high IS and P are observed in current timestep t = 4, and the constant high S of a vessel is observed in the previous two timestep at t = 3 and t =2 respectively. Similarly, the analysis in Table 3.3 and Figure 3.5 shows that the risk of high ice strength, i.e. *R of IS* = 0.8 at t = 4 in the Barents Sea is due to the presence of MFI, high IC, and ID is observed in current timestep t along with the presence of ID is observed in the previous timestep $t{-}1$ too. Furthermore, *R of IS = 0.5* at t = 2 and t = 5 in the region is due to the presence of high IC, OI, and ID are observed in current timesteps t, also the presence of ID is observed in the previous timesteps $t{-}1$ too. Moreover, R of the presence of P (Table 3.4 and Figure 3.6) in the region is due to the presence of F is observed in current timestep t and the presence of B is observed in both timesteps $t{-}1$ and $t{-}2$ respectively. Tables 3.2, 3.3, and 3.4 present the

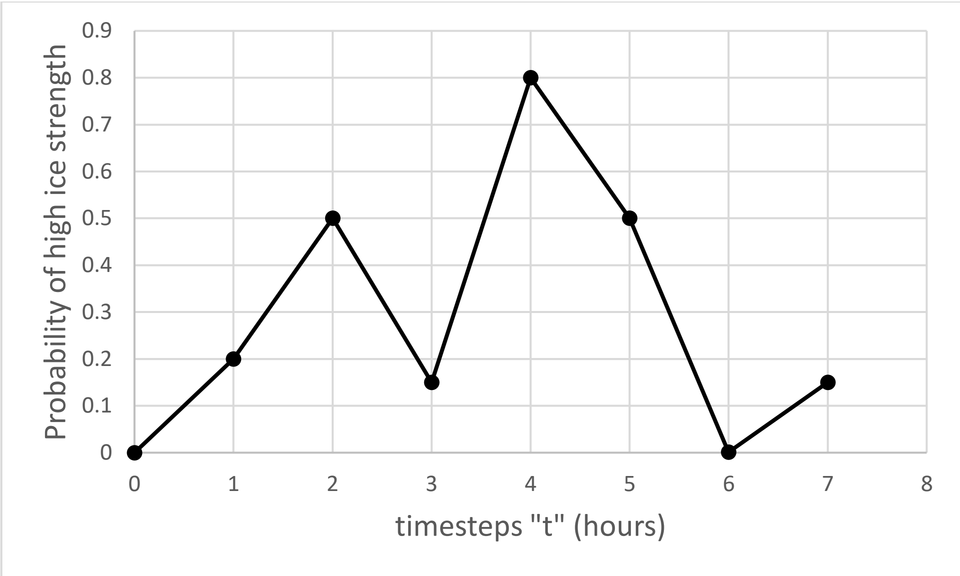

Figure 3.5. Risk of high *IS* in the Barents Sea (hour-to-hour variation).

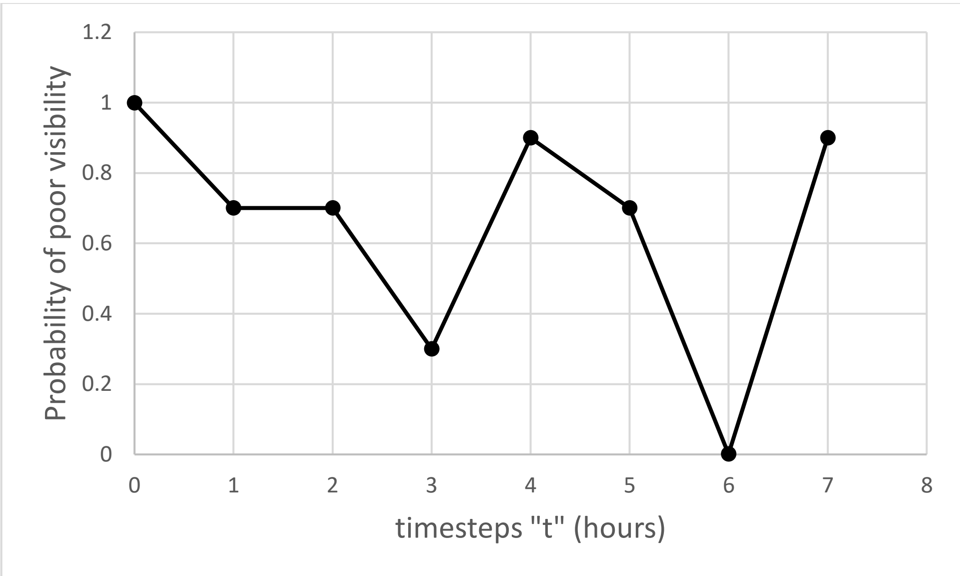

Figure 3.6. Risk of *P* in the Barents Sea (hour-to-hour variation).

Table 3.5. Effect of uncertainties of risk factors on the obtained risk.

Risk Factors	Minor	Moderate	Significant
F		x	
D		x	
B		x	
P		x	
IS		x	
ID		x	
IC		x	

complete picture of the risk of *C, IS,* and *P* and their dynamic evidence in the Barents Sea. Nevertheless, on the comparison of results in Tables 3.3 and 3.4 with the results of Table 3.2, it is revealed that such an increase in the *R* of high *IS* and the presence of *P* is hazardous for the vessels in the region and intensifies the risk of *C* in the region.

3.5.5 Uncertainty Analysis

Uncertainties are defined in terms of (1) Aleatory uncertainty, (2) Epistemic uncertainty. Aleatory uncertainty is associated with the occurrence of events, while epistemic uncertainty is associated with the lack of background knowledge about the events. The epistemic uncertainties can be reduced, but aleatory cannot and is sometimes called the irreducible uncertainty (Helton & Burmaster, 1996). The present study analyzes the epistemic uncertainty of the risk factors involved in the proposed methodology to see how the uncertainty affects the risk. Therefore, in the present study, we have used the semi-quantitative method presented by (Flage, R and

Aven, 2009). The authors provide the guideline for significant, moderate, and minor uncertainties as follows.

(1) Significant uncertainty: The involved phenomena are not well understood, risk factors that are used in the proposed methodology require strong simplification, data is not available or unreliable, and there is a lack of agreement among experts.
(2) Minor uncertainty: The involved phenomena are well understood, risk factors that are used in the proposed methodology are very reasonable, much reliable data is available, and there is a broad agreement among experts.
(3) Moderate uncertainty: The involved phenomena are well understood, but the model used in the study is not well understood, and some reliable data is available.

Nevertheless, the proposed model in the present study and its involved phenomena is well understood as it is explicitly explained in sections 3.3 and 3.4, however, due to the unavailability of the data, it is assumed that the effect of uncertainties on the obtained risk should be moderate (see Table 3.5). Besides, in many situations, there is some uncertainty, that may arise from the way, we observe the risk factors or collect the evidences, this additional uncertainty also affects the obtained risk in the region.

3.6 Conclusion

The present study proposes the risk-based model of the ship-ice collision scenario that is based on BN methodology. The model is later followed by an associated DBN model of the oil-tanker-ice collision scenario. The associated DBN model is applied to the winter navigation of the oil-tanker on the Barents Sea. The purpose of generating the associated DBN model of the main ship-ice collision model is to support the operational and navigational decisions while navigating on the Arctic waters in connection with time. Such time-oriented decisions are more vigorous in reducing ship-ice collision risks in the region.

The analysis reveals that the presence of moderate or high ice strength in the current timestep is significant to increase the risk of oil-tanker-ice collision in the Barents Sea. However, the presence of poor visibility in the current timestep and the high speed of the oil-tanker in the previous two timesteps are the other major factors that can increase the risk of collision in the region. The analysis also shows that the presence of different types of ice and high ice concentration in the current timestep and the presence of ice drift in either current or previous timestep can cause high/ moderate risk of ice strength in the region. The continuous presence of ice drift in the current, as well as the previous timesteps, also causes the risk of ice strength to increase. Such an increase in the risk of ice strength increases the risk of collision in the region. Also, the presence of fog or darkness in the current timestep can cause the risk of the presence of poor visibility. The presence of blowing snow in the previous two timesteps causes the visibility in the region, even more, worse and can produce extremely hazardous conditions for the vessels in the region.

In the present study, we have considered the environmental risk factors such as weather and ice in generating the ship-ice collision model because various risk factors that are operational or organizational do not change with respect to time, sometimes they exist within the system for years and cannot be identified as a safety issue unless they are explicitly examined. However, frequent hour-to-hour observations of weather and ice conditions in the Arctic can reduce the collision risk up to a reasonable extent. DBN methodology in maritime risk analysis studies is advantageous in such a way that it reduces the computational complexities by making the risk factors time-dependent, the methodology also provides support to decision making where data is not clear.

The DBN model proposed in this study can be extended to more than 8 timesteps. The proposed DBN model can be useful in route selection, it could be used to develop an early warning system that could help avoid the ship-ice collision. The collision probabilities and the hourly probabilities of ice strength and poor visibility that are obtained through the model could be helpful in decision making concerning safe operations in ice.

In the present study, the validity of the proposed DBN model has checked on the Barents Sea. However, with the little modification in the changing sea-ice and weather related conditions, the model can be applied to the other routes of the Arctic waters, for instance, the route from Murmansk to China that covers the important part of NSR, the Vilkitskii strait, and the routes of ice-infested waters of Atlantic Ocean, for instance, the St. Lawrence Seaway.

In order to get reliable results, it is necessary to have reliable prior beliefs. BNs and DBNs are only useful if the prior knowledge given to them is reliable; minor mistakes about the prior knowledge can distort the entire network and invalidate the results.

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Chapter 4

A cellular automation model for convoy traffic in Arctic waters[‡]

Co-authorship statement. A version of this chapter has appeared as an article in the journal titled *Cold Regions Science and Technology published by Elsevier*. The lead author, Bushra Khan, has developed the model, tested the model, analyzed its results and wrote the manuscript. Co-authors Dr. Faisal Khan and Dr. Brian Veitch supervised the study. They have made technical contributions by providing the conceptual understanding of the model and subsequently provided technical feedback, reviewed the model and results. All authors read and approved the final draft.

Abstract. Marine transportation in arctic waters involves risk due to the presence of ice, rapid weather changes, reduced visibility, and remoteness. Icebreaker assistance and ice-convoys are used to facilitate the safe navigation of commercial vessels transiting Arctic waters. The collision between individual ships, or a ship and an icebreaker, during a convoy is a potential danger. To study such risk, this paper presents an updated Nagel-Schrekenberg (NaSch) model of the marine convoy traffic integrated with a BN based probabilistic approach. This approach has been used to predict the maximum waterway density for the safe flow of traffic, and the collision probability during a convoy. The approach is tested here on a convoy in the Vilkitskii strait. The BN model proposed here could assist in assessing the failure probabilities of the causal factors and their contribution to collision likelihood. It may also be useful in developing a collision monitoring system that provides a real-time estimate of collision probability. The estimated probability could be used as an early warning for potential collisions, thus enhancing safe navigation and safety at sea.

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4.1 Introduction

Arctic waters are known for their challenges to marine transport. The presence of sea ice, long cold winters, short cool summers, strong winds, heavy blowing snow, waves, reduced visibility due to fog, long polar nights, and inadequacy of ship navigational systems due to remoteness contribute to the risk of Arctic marine transportation. To reduce such risks, the International Maritime Organization (IMO) has implemented the International Code for Ships Operating in Polar Waters (Polar Code), which came into force in 2017. The prime purpose of the Code is to deal with risks associated with design, construction, equipment, operational and training issues, search and rescue, and the environmental protection of the polar ecosystem (IMO, 2017).

Due to the growing interest in marine resources in the Arctic, such as fisheries, hydrocarbons, minerals, and tourism, and the potential for new shipping routes through the Arctic from Asia to Europe and North America, the opportunities for maritime activities in the Arctic are increasing (Eguíluz et al., 2016). Eguíluz et al. (2016) examined the maritime activities in the Arctic between 2010 and 2014 and reported that during 2014, a total of 11,066 ships were detected in the Arctic region, in which the majority of ships were supply, research, and survey vessels. The remaining were fishing, cargo, tanker, and passenger's vessels. (F. Khan et al., 2014) dynamically assessed transportation risk related to safe navigation in the Arctic by proposing a cause-consequence based model using BN: they estimated the probability of maritime accidents in the Arctic and their related consequences. Sahin and Kum (2015) described various risk factors in the Arctic and obtained numerical weights for each risk factor by using the fuzzy-AHP approach. They calculated the risk with probabilistic numerical levels. Marchenko, Borch, Markov, and Andreassen (2015) used risk matrices to assess frequencies and consequences of collision (with sea ice and other objects), grounding, fire, violence or terror for cruise ships, cargo ship, tankers, petroleum installations, and fishing boats in the Norwegian and the west Russian Arctic regions. Montewka et al. (2014) developed a framework for estimating the risk of maritime transportation in the Gulf of Finland. Their study focused on ship-ship collision in the open sea involving a RoPax vessel (Montewka et al., 2014). Kum and Sahin (2015) used a fuzzy fault tree analysis to investigate the root causes of Arctic marine accidents from 1993 to 2011. Smith, Veitch, Khan, and Taylor (2017) discussed ways to measure system performance of Arctic shipping operations in terms of their resilience. The authors proposed the functional resonance analysis method (FRAM) to identify sources of resilience and system vulnerabilities. B. Khan, Khan, Veitch, and Yang (2018) developed a quantitative risk assessment tool for ship-ice collisions using the OOBN method. Goerlandt, Montewka, Zhang, and Kujala (2017) investigated escort and convoy operations in ice conditions in Finnish waters using AIS and sea ice data. Their study focused on the relationship between the domain size of the ship and the existing ice conditions in the Gulf of Finland. They also investigated the escort and convoy speeds in Finnish waters with respect to the prevailing ice conditions.

The Arctic waters are only navigable for about three to three and a half months of the year, and most shipping activities are possible only with icebreaker escort. Icebreaker escort is sometimes organized to lead a convoy of ships. The possible collisions between the individual ships and between an icebreaker with the leading ship during a convoy put the crew and the ship at potential risk. The current study adopts the

Cellular Automata (CA) technique to study the marine convoy transportation risk. CA models are useful for simulating large systems (Q.-L. Li et al., 2016). Wolfram (1986) described CA as a regular uniform lattice (or array), usually infinite in extent (size), with a discrete variable at each site (cell). It evolves in discrete time steps, i.e., the value of the variable at one site is affected by the values of variables at sites in its neighborhood at the previous time step. The neighborhood is usually defined as the site itself and all the immediate adjacent sites. Based on the values of the variables in the neighborhood at the previous time step, and according to the definite sets of local rules, the variables at each site are updated simultaneously. According to (Straatman et al., 2001), CA models are very simple but have enough capacity to generate complex behaviors. According to (Fishwick, 1995), CA-based models are more generic than Partial Differential Equations (PDEs). CA has many applications in coastal zone management, ecology, computer science, and physical sciences. It is extensively used in the study of vehicle traffic flow (Qi et al., 2017b). For example, single-lane traffic has been modelled using the Nagel-Schreckenberg (NaSch) CA model in which the velocity of the vehicle is gradually increased by only one unit per timestep (Nagel & Schreckenberg, 1992). It is also used to model freeway road traffic flow. It provides a basic understanding of traffic flow regarding global density, and global flows of the vehicle that help in avoiding congestion and collisions in the lanes. Wright (2013), describes the global density ρ and global flow $J(\rho)$ as follows:

$$\rho = \frac{N}{n} = \frac{Number\ of\ vehicle}{number\ of\ sites} \tag{4.1}$$

$$J(\rho) = \frac{Number\ of\ vehicles\ passing\ a\ point}{number\ of\ timesteps} \tag{4.2}$$

It is capable of incorporating human behavior, which is a crucial factor when modeling traffic networks. It is a simple probabilistic CA model based on rule 184 (Wolfram, 1986; Wright, 2013). Rule 184 is a one-dimensional binary cellular automation rule; it forms the basis of many cellular automation models of traffic flow (Wolfram, 1986). In this model, particles that represent vehicles move in a single direction. Their starting and stopping depend on the vehicles in front of them (Wolfram, 1986). The number of particles remains unchanged during the simulation. The NaSch model is for single-lane traffic where vehicles cannot pass each other; there is no overtaking. With a little updating of the rules, the NaSch model can also be used in maritime traffic flow (Blokus-Roszkowska & Smolarek, 2015; Feng, 2013; Liu et al., 2010; Qi et al., 2017a).

To study the dynamics of the flow in the navigable channels of the Arctic, the present study uses the updated NaSch model of the marine convoy traffic. The updated model can be useful to predict the maximum density for the waterway; it can be helpful in avoiding the ship-ship and ship-icebreaker collision during a convoy. The updated NaSch model integrated with a BN model is further helpful in relating the macroscopic properties of the system- such as *Maximum velocity,* v_{max}, *Deceleration probability,* $p_{deceleration}$, and *Critical density,* $\rho_{critical\ density}$ of the traffic flow- with the main factors for convoy safety-such as *Maintaining a safe distance between 2 ships, Safe operations in ice, Maintaining a safe speed in ice, and Maintaining a safe distance between an icebreaker and a leading ship* during a convoy. The outcome of the integrated model is the estimation of critical density for the flow of convoy traffic, and collision probability (ship-ship and ship-icebreaker) during a convoy. The remainder of the paper is structured as follows: Section 4.2 presents the methodology, section 4.3 presents the simulations and results, and section 4.4 discusses the conclusion of the study and future work.

4.2 Collision accident modeling methodology

Figure 4.1 shows the generic framework proposed for the study.

4.2.1 NaSch model

The classical NaSch model consists of a one-dimensional grid of L sites. The sites can be empty or occupied by a single vehicle of velocity zero to v_{max}, when the velocity of a vehicle is considered to be in integers (Wright 2013). Periodic boundary condi-

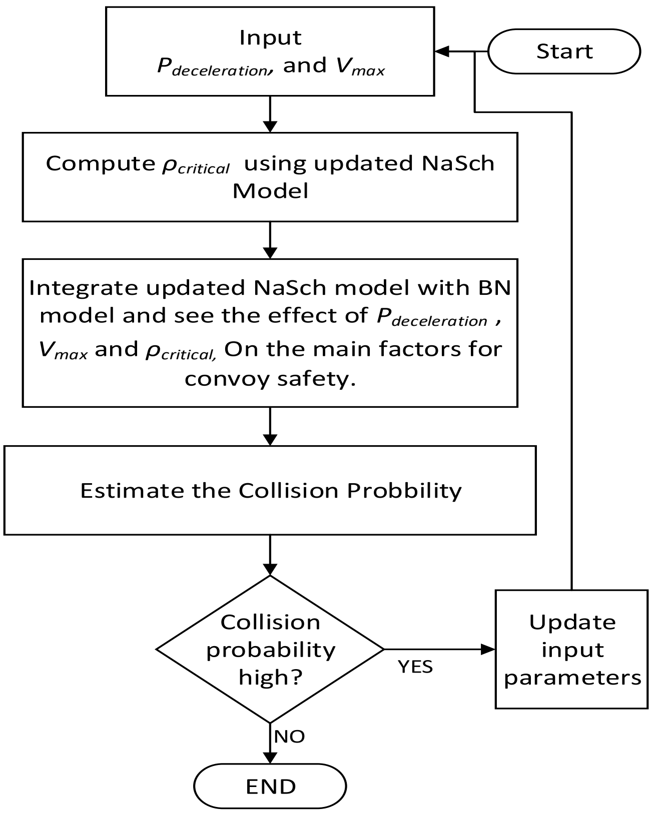

Figure 4.1. Proposed Cellular Automata based framework for marine convoy traffic accidents

tions have been adopted for this model. No vehicle can overtake. Periodic boundary conditions are the set of boundary conditions that are used to approximate a large or infinite system into unit cells. The NaSch model consists of a set of four rules. The rules must be applied for each iteration T_e (timestep) in the direction of travel (Wright 2013). The rules of the NaSch model for single-lane traffic (Nagel & Schreckenberg, 1992; Wright, 2013) are stated as follow

- Acceleration: If a vehicle n has a velocity v_n, and v_n is less than the maximum velocity v_{max}, the vehicle will increase its velocity by one unit

$$v_n < v_{max}; v_n = v_n + 1 \qquad (4.3)$$

- Deceleration to avoid accidents: If a vehicle *n* is at site i, and the next vehicle is at site $i + d$, and after step 1, the velocity of *n*th vehicle i.e. v_n is greater or equals to d, the velocity of the vehicle v_n is reduced according to

$$if\ v_n \geq d;\ v_n = d - k \qquad (4.4)$$

  where, d is the space between the *i* th and *(i+1)*th vehicle, and k is the minimum safe distance between the two vehicles. In NaSch model, $k = 1$ that is the minimum safe distance between two vehicles is 1 cell.

- Randomization (reaction): For a given deceleration probability $p_{deceleration}$, the velocity v_n of the vehicle n is reduced as follows:

$$v_n = v_n - 1\ for\ p_{deceleration} \qquad (4.5)$$

- Move forward: A vehicle n at a site x_n moves forward by a number of steps equal to its velocity v_n:

$$for\ v_n\ ; x_n = x_n\ + v_n \tag{4.6}$$

4.2.2 Updated NaSch model with respect to a marine convoy traffic

In a marine convoy traffic, ships are required to maintain a safe zone between each other and between the icebreaker and the leading ship of the convoy, to avoid collisions. The required safe zone is known as the ship domain (Fujii & Tanaka, 1971; Liu et al., 2016; Pietrzykowski & Uriasz, 2009; Toyoda & Fujii, 1971; N. Wang, 2013; Y. Wang & Chin, 2016). The ship domain is used to define the safe distance between ships (Liu et al., 2010). According to recent research, the ship domain is dynamic (Liu et al., 2016; Pietrzykowski & Uriasz, 2009; Y. Wang & Chin, 2016), as environmental conditions such as harsh weather and ice, velocity, size, operational and navigational skills, and waterway conditions all are factors that can affect the size of ship domain (Qi et al., 2017a).

In the present study, the waterway for convoy traffic is divided into *n* sites. Each site can only contain one ship at a time with a velocity of zero to v_{max}. Ship traffic is heterogeneous, so most of the time, the maximum velocity v_{max} of different ships varies (Qi et al., 2017a), and can be influenced by factors such as harsh weather, ice, operational and navigational states of the ships, and human action, any of which can cause the ship to decelerate. The same phenomena also occur in other types of traffic (Nagel & Schreckenberg, 1992; Wright, 2013), but the causes are different. This phenomenon is called the randomization, and $p_{deceleration}$ is called the randomization deceleration probability (Nagel & Schreckenberg, 1992; Qi et al., 2017b; Wright, 2013).

In the proposed framework, we have estimated the critical density with respect to the deceleration probability and maximum velocity of the system and then integrate the proposed framework of updated NaSch model with the BN. The integrated model is used to assess the risk of collision in the marine convoy traffic navigating on the Arctic waters. Assumptions of the updated NaSch model are; if v_n is the velocity of the *n*th ship in a convoy, d_n is the space that the *n*th ship gives to its preceding ship p, $k_{safe,n}$ is the minimum safe distance between ship n and the preceding ship p during a convoy, v_p is the velocity of the preceding ship in a convoy, and v_{max} is the maximum velocity of ships in a convoy. The updated rules of the proposed model with respect to the stated assumption can be defined as follows:

- Acceleration:

  $$If\ d_n > k_{safe,n}\ then, v_n(t) = v_n\,(t) + 1;\ v_n(t) < v_{max} \tag{4.7}$$

  Eq. 4.7 reflects the behavior of a ship operator in a convoy to attain the maximum speed.

- Deceleration:

  $$\text{if } d_n < k_{safe,n}\ then, v_n\,(t) = d_n - k_{safe,n};\ k_{safe,n} = 1 \text{ cell} \tag{4.8}$$

- Randomization: For a given deceleration probability $p_{deceleration}$, the velocity v_n of the *n*th ship is reduced as

  $$v_n(t) = v_n(t) - 1 \text{ for } p_{deceleration} \tag{4.9}$$

  Ships in a convoy may decelerate due to harsh weather, ice, operational and navigational states of the ships, and operator's action.

- Move Forward (location update): After the above steps, the location of the nth ship at t is $x_n(t)$, the velocity of the nth ship at $t + 1$ is $v_n(t + 1)$, thus at $t + 1$, the location of the nth ship in a convoy is defined as follows

$$x_n(t + 1) = x_n(t) + v_n(t + 1) \tag{4.10}$$

Eqs. (4.3) to (4.10) are based on the general properties of the single traffic lane. Wright (2013) further explains the equations as follows: Eqs. (4.3) and (4.7) reflect the behavior of the operators who want to attain the maximum possible velocity v_{max} with acceleration equal to 1. Eqs. (4.4) and (4.8) intend that vehicles do not crash: according to both equations, the speed of the nth vehicle v_n should be equal to or greater than the minimum safe distance between the two vehicles in a convoy. If the distance between the two vehicles in a convoy is shorter than the minimum safe distance, a collision is more likely to occur (Goerlandt, Montewka, et al., 2017). Eqs. (4.5) and (4.9) add randomness, which is essential to simulating traffic flow, enabling, for example, traffic jams. Eqs. (4.5) and (4.9) indicate that a vehicle could randomly decelerate for a given $p_{deceleration}$. $p_{deceleration}$ is a stochastic component introduced in the NaSch model by randomization, which considers the non-deterministic motion of vehicles due to the operators' behavior. Eqs. (4.6) and (4.10) allow the vehicles to move forward along the route.

4.2.3 Bayesian Network

A BN is based on direct dependencies between a set of variables. These dependencies are shown in the form of a directed graph and the set of node probability tables (NPT). The directed graph consists of sets of nodes and arcs. The nodes correspond to variables, while arcs are directly used to link the variables. For example, in Figure 4.5 the arcs from the nodes *Maintaining a safe speed in ice* to *Maintaining a safe distance between 2 ships* and *maintaining a safe distance between an icebreaker and a leading ship* show that there is a causal dependence of *Maintaining a safe speed in ice* on *Maintaining a safe distance between 2 ships* and *Maintaining a safe distance between an icebreaker and leading ship.* The node *Maintaining a safe speed in ice* is then said to be a parent node of nodes *Maintaining a safe distance between 2 ships* and *Maintaining a safe distance between an icebreaker and a leading ship*. BN are directed acyclic graphs (DAG), i.e. the graphs have no cycles. For example, in a graph G, if there is an arc from the node *A* to *B* and an arc from *B* to *C,* then there cannot be an arc from *C* to *A*. In DAG, each node *A* has an associated probability table called the node probability table (NPT) of the node *A*. This is the probability distribution of *A* given the set of the parents of *A*, *i.e.*

$$P(A|A_1, A_2, \dots\dots\dots\dots\dots. A_n), \tag{4.11}$$

where A_1, A_2, …, A_n are the parents of *A*. Moreover, if node *A* has no parents, then it is called the root node, and in this case, the NPT of *A* is merely the probability distribution of *A* (Fenton & Neil, 2013). NPTs that are assigned to the nodes show the conditional dependencies between the variables. BN allows updating of prior probabilities based on new information.

4.3 Testing the model at Vilkitskii Strait

The updated NaSch model enables us to obtain the $\rho_{critical\ density}$ of marine convoy traffic in Arctic waters. In this section, the proposed model is applied to a convoy

Table 4.1. Estimation of critical densities $\rho_{critical\,densities}$ of marine convoy traffic at Vilkitskii strait with respect to the varied maximum velocities v_{max} and deceleration probabilities $p_{deceleration}$.

v_{max}	$p_{deceleration}$	$\rho_{critical\,density}$
1	0.01	0.50
3	0.01	0.25
3	0.10	0.22
3	0.30	0.18
5	0.02	0.18
5	0.24	0.12
5	0.01	0.18
5	0.30	0.10

navigating through the Vilkitskii strait. The Vilkitskii strait is along the NSR; it is the primary connection between the Kara and the Laptev Sea. It has a length of 60 nautical miles and depth of 100 to 200 meters. Ships of any size and draft can pass through it (Østreng et al., 2013). The Strait is typically navigable from July to October. We divide the length of Vilkitskii strait into 200 equal sites/cells (i.e. n =200 cells), so each cell has a length of 556m. We take 200 iterations i.e. (T_e = 200), where each T_e is approximately 1 second (an approximation of the response time of a ship operator).

Russia has opened new export opportunities for commercial shipping through NSR, such as for oil tankers, gas and bulk carriers, and cargo ships bringing materials for industrial and mining activities (ABS advisory, 2014). In the current study, we assume a convoy comprised of 10 vessels – assumed to be oil tankers and bulk carriers - transiting the NSR from Vilkitskii strait lead by an icebreaker.

The results of the simulation show that the $\rho_{critical\,density}$ of the flow is smaller for the larger values of v_{max} and $p_{deceleration}$. Increasing v_{max} and $p_{deceleration}$ cause the maximum flow and mean velocity of the system to collapse at lower densities, leading to sudden traffic jams and possible collisions (Figures 4.2-4.4, and Table 4.1).

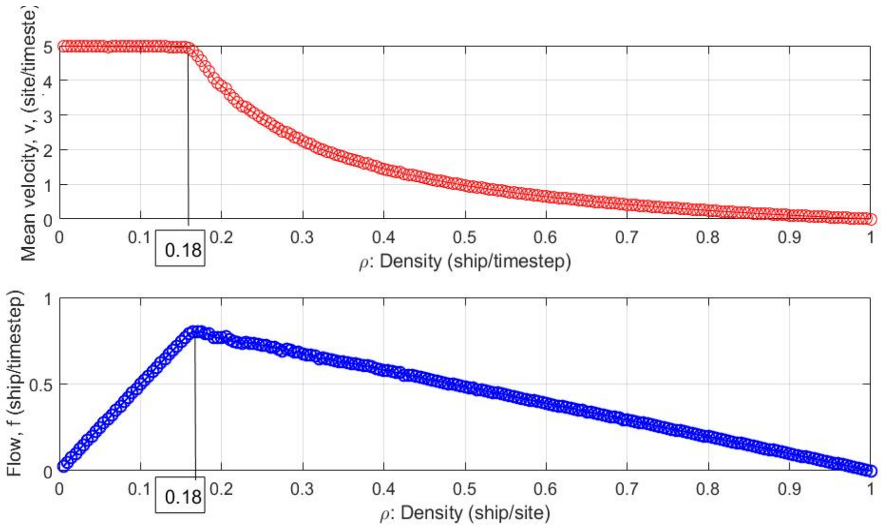

Figure 4.2. Simulation results of marine convoy traffic at Vilkitskii Strait using updated NaSch model with $p_{deceleration} = 0.02$, $v_{max} = 5$, $n = 200$, and $T_e = 200$ (a) Mean velocity, v vs Density, ρ, (b) A fundamental density-flow diagram.

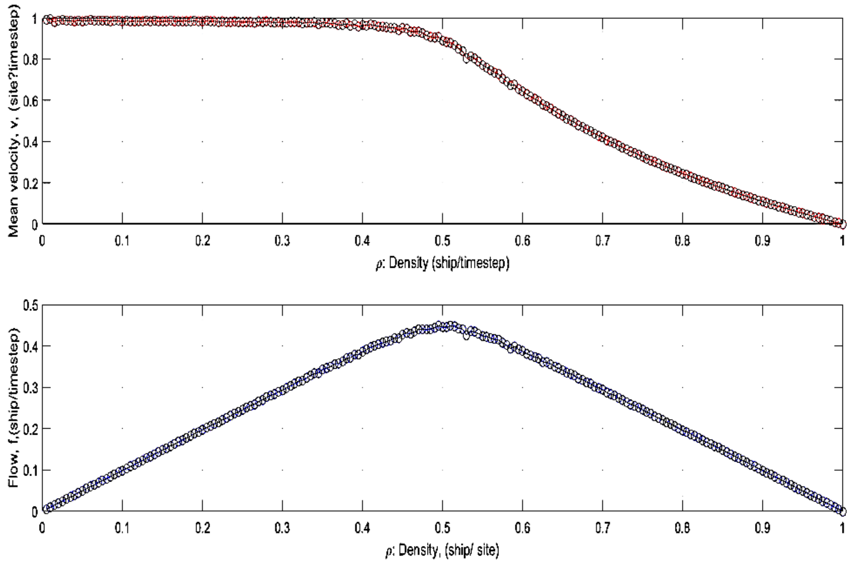

Figure 4.3. Simulation results of marine convoy traffic at Vilkitskii Strait using updated NaSch model with $p_{deceleration} = 0.01$, $v_{max} = 1, n = 200$, and $T_e = 200$, (a) Mean velocity, v vs Density, ρ, (b) A fundamental density-flow diagram.

Figure 4.3 shows the relationship is symmetric due to the particle-hole symmetry (Schadschneider & Schreckenberg, 1993) that has broken at $v_{max} > 1$ (Wright, 2013). A BN model is constructed to see the effect of $p_{deceleration}$, v_{max}, and $\rho_{critical\ density}$ on the main factors for the convoy safety at the strait, i.e. *Maintaining a safe distance between 2 ships, Safe operations in ice, Maintaining safe speed in ice,* and *Maintaining a safe distance between an icebreaker and a leading ship* during a convoy (see section 4.1). The factors are Boolean nodes in the BN that take values from the set $\{$Yes, No$\}$. The nodes *Deceleration probability* $p_{deceleration}$, and *Maximum velocity* v_{max} take values from the set $\{$High, Medium, Low$\}$. The node *Critical density* ($\rho_{critical\ density}$) takes values from the set $\{$System collapse at lower density, System does not collapse at lower density$\}$. For illustration purpose, let $v_{max} = 5\text{ (high)}, 3\text{ (medium)}, \text{and } 1\text{ (low)}$ (see Figure 4.5). The BN is also used

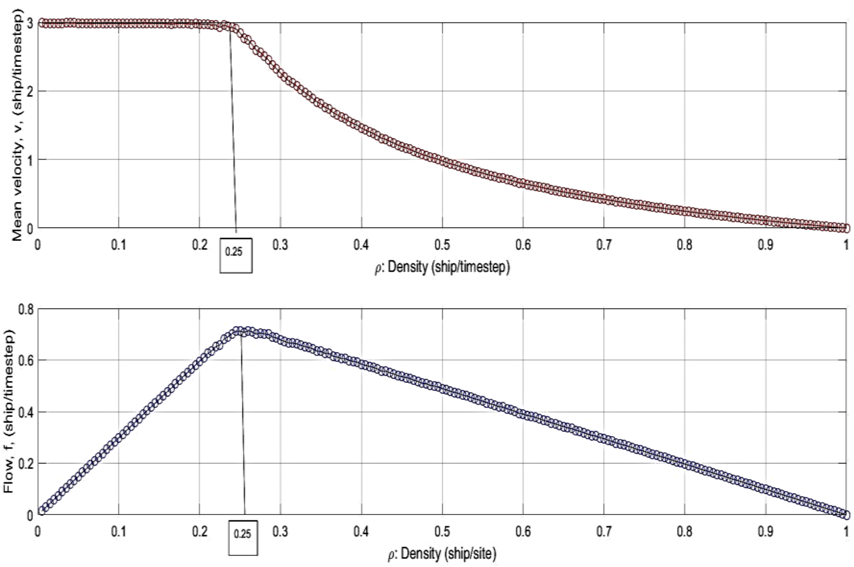

Figure 4.4. Simulation results of marine convoy traffic at Vilkitskii Strait using updated NaSch model with $p_{deceleration} = 0.01$, and $v_{max} = 3, n = 200$, and $T_e = 200$, (a) Mean velocity, v vs Density, ρ, (b) A fundamental density-flow diagram.

to estimate the probability of collision (ship-ship/ ship-icebreaker) during a convoy (see Figure 4.5). The software AgenaRisk (2016) is used in this study to develop the BN model and perform related computations. The conditional probability tables in the proposed BN model are constructed as follows:

(1) The node *Critical density* is dependent on the input nodes *Deceleration probability* and *Maximum Velocity.*

(2) The node *Critical density* derives the nodes *Maintaining a safe distance between two ships in a convoy* and *Maintaining a safe speed in ice.*

(3) The node *Maintaining a safe distance between two ships in a convoy* is also dependent on *Maintaining a safe speed in ice.*

(4) The node *Safe Operation in ice* in the model is dependent on *Maintaining a safe distance between two ships in a convoy* and *Maintaining a safe distance between an icebreaker and the leading ship of a convoy.*

(5) The node *Maintaining a safe distance between an icebreaker and the leading ship of a convoy* is dependent on *Maintaining a safe speed in ice.*

(6) The output node *Collision* in the model is dependent on *Maintaining a safe distance between two ships in a convoy* and *Maintaining a safe distance between an icebreaker and the leading ship of a convoy.*

4.3.1 Estimation of collision probability

Operators of ships in a convoy are responsible for maintaining a safe distance and speed between the adjacent vessels. The commanding officer of the icebreaker will assign the required distance to be maintained between itself and the leading ship of the convoy (Canadian Coast Guard, 2012a). In this section, we consider the effect of the $p_{deceleration}$, v_{max}, and $\rho_{critical\ density}$ on the main factors for convoy safety. At low $p_{deceleration}$ and low v_{max}, there is a 90% chance that the system will not collapse at the lower densities (see Figure 4.5). The result also agrees with Table 4.1. This will increase the chance of avoiding collisions during a convoy.

The Estimated Collision Probability (C) in this study is 0.0128 (see Figure 4.5). The failure probabilities of the nodes in the BN (Figure 4.5) and their effect on the

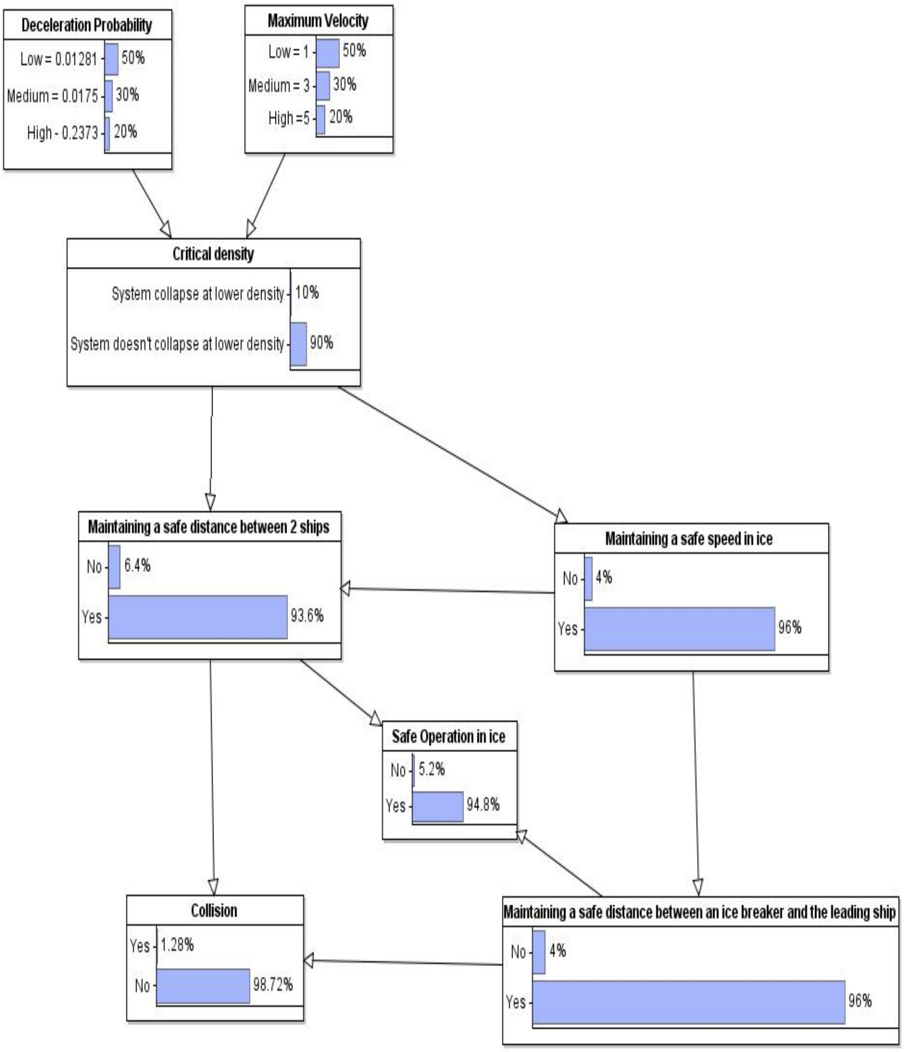

Figure 4.5. BN of Estimated Collision probability (C) during a convoy at Vilkitskii strait.

Table 4.2. Failure probabilities of the nodes and their effect on Estimated Collision Probabilities

Ranking	Nodes in BN	Failure probabilities of the nodes for Estimated Collision probabilities C, C1, C2, C3				Effect of the nodes on Estimated Collision Probabilities C, C1, C2, C3 (% contribution) (sensitivity analysis)			
1	Maintaining a safe distance between 2 ships.	0.064	0.096	0.077	0.200	20.0	20.0	20.0	20.0
2	Safe operation in ice.	0.052	0.078	0.062	0.160	20.0	20.0	20.0	20.0
3	Maintaining a safe speed in ice.	0.040	0.060	0.050	0.120	20.0	20.0	20.0	20.0
4	Maintaining a safe distance between an icebreaker and a leading ship.	0.040	0.06	0.048	0.120	20.0	20.0	20.0	20.0
5	Critical density.	0.100	0.150	0.120	0.310	12.0	12.8	12.8	12.8
6	Deceleration probability.	0.200	0.300	0.200	0.200	6.00	6.40	7.70	9.00
7	Maximum velocity.	0.200	0.200	0.300	0.200	2.00	3.80	2.60	6.40

Table 4.3. Input data for the Estimated Collision *C*

Deceleration probability			Max. velocity			Critical density		Maintains a safe speed in ice		Maintaining safe distance between two ships		Safe operation in ice		Safe distance between an icebreaker and a ship by maintaining a safe distance between them		Collision	
$p_{deceleration}$			v_{max}			$\rho_{\ density}$										C	
L	M	H	L	M	H	L	H	Y	N	Y	N	Y	N	Y	N	Y	N
0.5	0.3	0.2	0.5	0.3	0.2	0.1	0.9	0.96	0.04	0.936	0.064	0.948	0.052	0.96	0.04	0.0128	0.987

Table 4.4. Estimated collision C1 due to the change in the input values of Deceleration probability.

Deceleration probability			Max. velocity			Critical density		Maintains a safe speed in ice		Maintaining safe distance between 2 ships		Safe operation in ice		Safe distance between an icebreaker and a ship		Collision	
$p_{deceleration}$			v_{max}			$\rho_{density}$										C1	
L	M	H	L	M	H	L	H	Y	N	Y	N	Y	N	Y	N	Y	N
0.4	0.3	0.3	0.5	0.3	0.2	0.15	0.85	0.94	0.06	0.904	0.096	0.922	0.078	0.94	0.06	0.0192	0.9808

Table 4.5. Estimated collision C2 due to the change in the input values of maximum velocity.

Deceleration probability			Max. velocity			Critical density		Maintains a safe speed in ice		Maintaining safe distance between 2 ships		Safe operation in ice		Safe distance between an icebreaker and a ship		Collision	
$p_{deceleration}$			v_{max}			$\rho_{density}$										C2	
L	M	H	L	M	H	L	H	Y	N	Y	N	Y	N	Y	N	Y	N
0.5	0.3	0.2	0.4	0.3	0.3	0.12	0.88	0.95	0.05	0.92	0.077	0.94	0.062	0.95	0.048	0.0154	0.985

Table 4.6. Estimated collision C3 due to the change in the input values of critical density.

Deceleration probability			Max. velocity			Critical density		Maintains a safe speed in ice		Maintaining safe distance between 2 ships		Safe operation in ice		Safe distance between an icebreaker and a ship		Collision	
$p_{deceleration}$			v_{max}			$\rho_{density}$										C2	
L	M	H	L	M	H	L	H	Y	N	Y	N	Y	N	Y	N	Y	N
0.5	0.3	0.2	0.5	0.3	0.2	0.31	0.69	0.88	0.12	0.8	0.2	0.84	0.16	0.88	0.12	0.4	0.96

Estimated Collision C can be seen in Table 4.2. Table 4.3 shows the input data for C. Table 4.2 also shows the failure probabilities of the nodes for C1, C2, and C3. These failure probabilities can be obtained by taking different input values of macroscopic properties in the BN (see Tables 4.4, 4.5, and 4.6). Tables 4.4, 4.5, and 4.6 show that a small change in the values of macroscopic properties can have a profound impact on the factors for convoy safety. It is also observed that the macroscopic properties of the system contain less sensitive values for all C, C1, C2, and C3, but are exclusively responsible for the failures of the factors for convoy safety. The failures of all the factors are equally sensitive for the collisions during a convoy (see Table 4.2). For the present study, data values for the BN are estimated from the case study of oil tanker-ice collision proposed by B. Khan et al. (2018) and experts' opinion.

4.4 Conclusions

The study presented a NaSch model adapted to marine convoy traffic. The proposed model was used to estimate the critical densities for convoys transiting Arctic waters to avoid jams and collisions. The model further combined with a BN model to see the effect of certain macroscopic properties of marine convoy traffic on the main factors for convoy safety. The integrated model was also used to estimate the collision probabilities for convoys in Arctic waterways. The utility of the proposed model was established through the simulation of a convoy of 10 oil tankers and bulk carriers passing through the Vilkitskii strait. The study observed that increasing $p_{deceleration}$ and v_{max} cause the maximum flow and mean velocity of convoy traffic to drop at lower densities, resulting in sudden traffic jams and possible collisions during a convoy. The study observed that lower *Critical densities* with high *Deceleration probabilities* and *Maximum velocities* are wholly responsible for the failures of the main factors for convoy safety. A slight change in the values of macroscopic properties can significantly affect the main factors for safety. All these factors are equally sensitive to collision. It was also observed in the study that high *Densities* along with the lower *Deceleration probabilities* and *velocities* prevent the factors for convoy safety from failure and avoid jams and collision during a convoy.

The proposed model provides a new perspective of the dynamics of Arctic Navigation, and an opportunity to monitor collision probability in real-time. The estimated probability can be used as a mechanism to develop an early warning and collision avoidance system. It can be useful in decision making concerning safe convoy operations, such as maneuvering, route selection, towing, and escorting. The estimated probability can also be useful in the selection of safe speed, maintaining a safe speed during a convoy, and maintaining a safe distance between the icebreaker and the leading ship of the convoy and the ships within the convoy.

The proposed model simplifies maritime accident modeling by developing a practical understanding of the role of macroscopic properties of the traffic flow in maritime convoys. It is also helpful in predicting the maximum density of any given waterway for the safe flow of traffic. The developed model can be used as a guiding tool to control and minimize the navigational and operational risk in Arctic waters. The proposed updated NaSch model study has some limitations that need to be addressed i.e. it cannot be used for two-way traffic. Also, in the integrated model, the maximum safe distance between two ships must be calculated according to the prevailing ice conditions in the waterways, harsh weather, and operational and navigational states of the ships in the convoys. The application of the current updated CA model of marine convoy traffic needs to be extended further to overcome such limitations in future. In the present study, the validity of the proposed model has checked on the Vilkitskii strait. However, the model can also be applied to the other routes of the Arctic waters, for instance, the route from Murmansk to China in NSR, the routes of Barents Sea, and the routes of ice-infested waters of Atlantic Ocean, for instance, the St. Lawrence Seaway.

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Chapter 5

Integrated accident model for marine convoy traffic in ice-covered waters[§]

Co-authorship statement. A version of this chapter is accepted for publication in the *International Journal of Maritime Engineering*, published by The Royal Institution of Naval Architects. The lead author, Bushra Khan, has developed the model, tested the model, analyzed its results and wrote the manuscript. Co-authors Dr. Faisal Khan and Dr. Brian Veitch supervised the study. They have made technical contributions by providing the conceptual understanding of the model and subsequently provided technical feedback, reviewed the model and results. All authors read and approved the final draft.

Summary. Independent safe navigation in ice-covered water is difficult. Icebreaker assistance is required for sailing through ice-covered waters. This poses an additional risk of collision. The study proposes a modified Human Factor Analysis and Classification (HFACS) framework to identify and classify contributing risk factors during a convoy. HFACS integration with Nagel-Schrekenberg (NaSch) model considers an operator's behaviour and links it with the occurrence of various risk factors. The study finds significant influence in risk from small changes in two new factors, viz., crew reduction and crew overload. For example, based on the sensitivity analysis, it is determined that about a 17% contribution of crew reduction and about a 24% of contribution of crew overload increase the contribution of risk taking by an amount of approximately 93% in the overall risk of accidents. The accident probabilities obtained here will be helpful in decision making concerning safe operations during a convoy.

[§] Khan, B., Khan, F., & Veitch, B. (2020). Integrated accident model for marine convoy traffic in ice-covered waters. Accepted for publication in the *International Journal of Maritime Engineering (RINA Transactions Part A)*.

5.1 Introduction

Icebreaker assistance is used extensively to support shipping in ice-covered waters, including icebreaker escort of single or several ships (M. Zhang et al., 2019). Such operations are useful for reducing the risk of vessel-ice damage during ice navigation. If the distance between the ships and the icebreaker is not maintained appropriately, collision accidents could occur between the icebreaker and a leading ship, and between the assisted ships during a convoy. Valdez Banda (2017) showed that 48% of accidents in the Baltic Sea and 55% of accidents in the Northern Sea Route (NSR) have occurred under the same icebreaker assistance conditions.

Khan *et al.* (2019) studied the dynamics of the traffic flow in navigable channels. The authors proposed an updated Nagel-Schrekenberg (NaSch) model to estimate the critical densities of the convoys to avoid sudden traffic jams and collisions during a convoy in Arctic waterways. They tested the model on the Vilkitskii strait and combined it with a BN model to estimate the ship-ship and ship-icebreaker collision probability during a convoy. Goerlandt *et al.* (2017) investigated the escort and convoy operations using Automatic Identification System (AIS) and sea ice data. They also investigated the escort and convoy speeds with respect to the prevailing ice conditions in the Gulf of Finland. The authors focused on the relationship between the domain size of the ship and the existing ice conditions in the Gulf. Ship domain is a safe distance between ships in a convoy, while ships are required to maintain a safe zone between each other and between the icebreaker and the leading ship of a convoy (B. Khan et al., 2019).

Human errors are often recognized as a main cause of accidents (Chen & Chou, 2012; Islam et al., 2016, 2020; B. Khan et al., 2018; Rothblum, 2000). According to the statistics, human error contributes 84-88% in tanker accidents, 79% in towing vessel groundings, and 89-96% in collisions (Transportation Safety Board of Canada, 1993). Islam *et al.* (2018, 2017) applied human error assessment during maintenance operations of marine systems. Similar to aviation accidents (Wiegmann & Shappell, 2003), HFACS is also used in various marine investigations, including HFACS-MA, HFACS-Grounding, HFACS-SIBCI (Chen & Chou, 2012; Mazaheri et al., 2015; M. Zhang et al., 2019, 2018) as well as railway accident investigations (Baysari et al., 2008; Reinach & Viale, 2006). An HFACS framework is specifically developed to define the relevant active and latent failures in Reason's swiss cheese model (Wiegmann & Shappell, 2003). Initially, it contains four layers of risk levels: (1) unsafe acts, (2) precondition for unsafe acts, (3) unsafe supervision, and (4) organizational factors, together with 19 classifications. Reinach and Viale (2006) proposed a fifth layer called the *external factors.* The authors believed that the economy, law, and policy should also be considered during the identification of accident risk factors. Later, other authors also used the five-layer HFACS model in their studies to identify the risk factors, such as HFACS-Ground (Mazaheri *et al.*, 2015) and HFACS-SIBCI (M. Zhang et al., 2019, 2018). The layers in HFACS model are hierarchical: each layer is dependent on the previous one and factors are believed to make progress from active to latent conditions as they progress up the hierarchy from unsafe acts to external influences.

The present study has proposed a five-layer Human Factor Analysis and Classification System-Marine Convoy Traffic and Accident in Ice-covered waters (HFACS-MCTAI) model with 21 classifications. Changes have been proposed in preconditions for unsafe acts, unsafe supervision, organizational factors, and external factors, on the basis of which accident risk factors can be identified and classified. The cause-consequence relationship between risk factors has been developed to estimate the accident probabilities of unsafe acts, preconditions of unsafe acts, unsafe supervision, organizational factors, and external factors during a convoy navigation. The updated

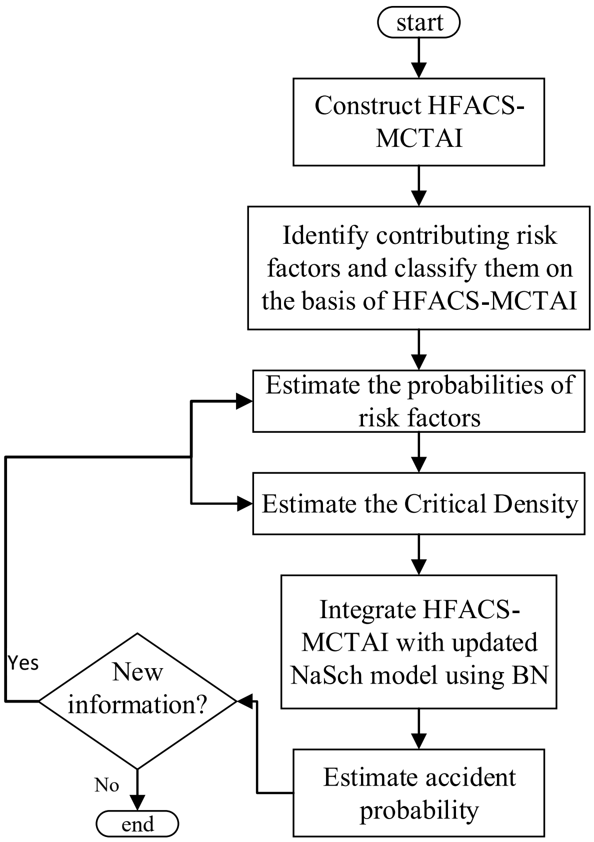

Figure 5.1. Generic framework for Marine Convoy Traffic Accidents in Ice-covered waters.

NaSch model (B. Khan et al., 2019) is used to estimate the critical density of the convoy traffic in order to avoid traffic jams and collisions in ice-covered waters. Next, the updated NaSch and HFACS-MCTAI models are integrated in a BN and form a model called the Integrated Accident Model (IAM) for Marine Convoy Traffic in Ice-covered Waters. This integrated model extends the concept of an operator's behaviour during a convoy by adding the knowledge of various risk factors that are identified and classified through the proposed HFACS-MCTAI model. Further, the model is also extended to observe the effects of unsafe acts, preconditions for unsafe acts, unsafe supervision, organizational factors, and the external factors on critical density, maximum velocity, deceleration probability and a sudden traffic jam during a convoy in ice-covered waters. Also, the model estimates the accident probabilities of collision between two ships, ship-ice collision, and collision between an icebreaker and the leading ship in a convoy. The proposed methodology is applied to a case study that involves convoying through the St. Lawrence Seaway. The remainder of the paper is structured as follows: section 5.2 presents the methodology, section 5.3 presents the results and discussions, and section 5.4 discusses the conclusions of the study.

5.2 The Framework to Develop Integrated Accident Model

Figure 5.1 presents the general framework of the proposed collision risk model. In the following sections, the main components of the proposed framework are discussed in detail.

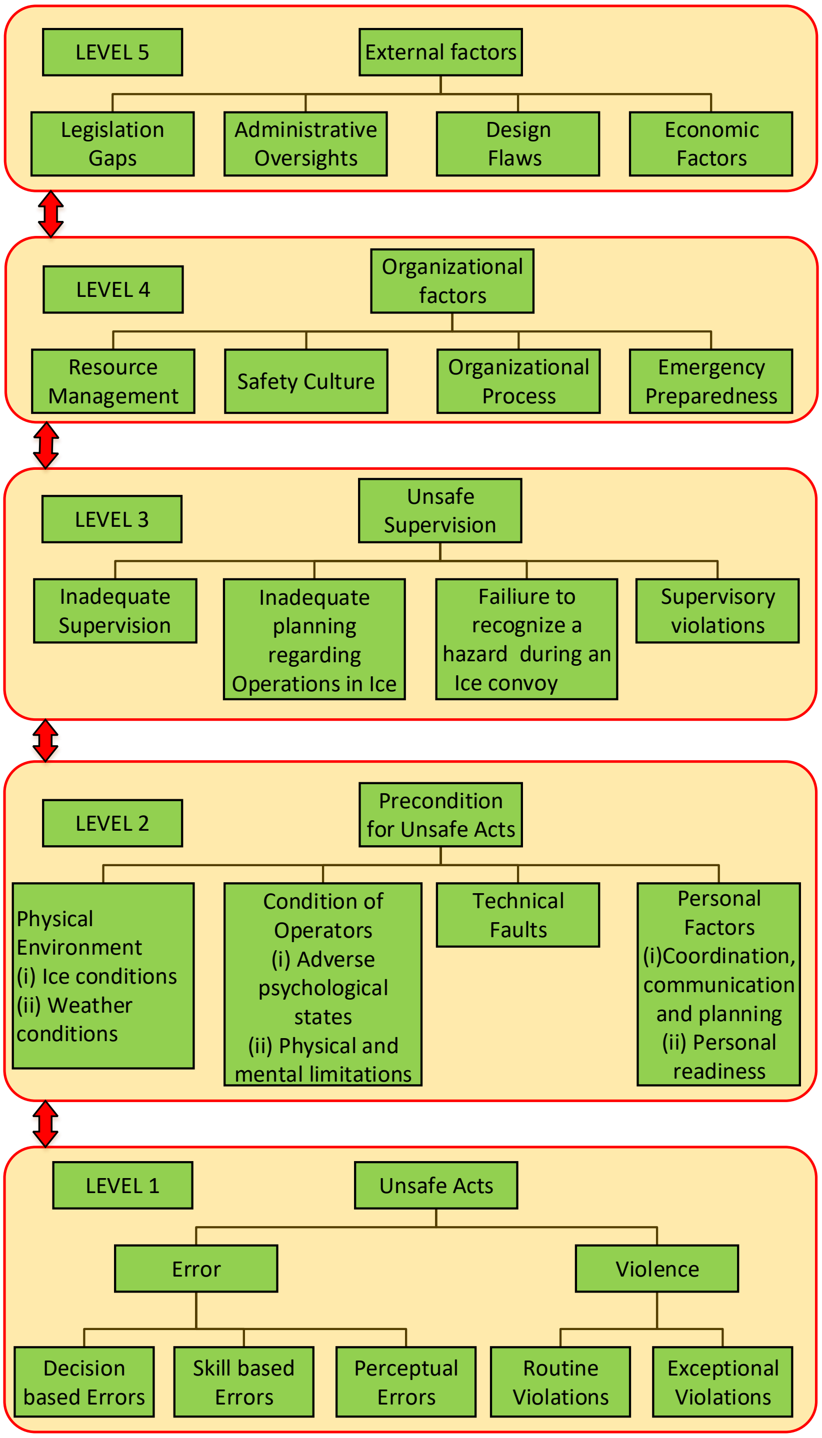

Figure 5.2. HFACS-MCTAI model.

5.2.1 HFACS-Marine Convoy Traffic and Accidents in Ice-covered waters (HFACS-MCTAI) model

This section presents the HFACS-MCTAI model adapted from Wiegmann and Shappell (2003). The proposed model has five layers of accident risk levels: (1) unsafe acts of the operators, (2) preconditions for unsafe acts, (3) unsafe supervision, (4) organizational factors, and (5) external factors. The risk levels have 21 classification categories (see Figure 5.2). Some changes have been made in the second, third, fourth, and fifth layer of the proposed HFACS-MCTAI model. The changes are briefly discussed as follows:

i. The classification category, technical faults (B. Khan et al., 2018) has been introduced to the second layer of the proposed HFACS-MCTAI model.

ii. Two classification categories, inadequate planning regarding operations in ice, and failure to recognize a hazard during a convoy have been introduced to the third layer of the proposed HFACS-MCTAI model, instead of planned inappropriate operations, and failure to correct problem of the original HFACS model.

iii. We replace the classification category organizational climate with safety culture in the fourth layer of the proposed HFACS-MCTAI model. organizational climate can be viewed as the overall working environment within the organization, while safety culture actually refers to unspoken rules, values, attitudes, beliefs and customs of an organazation (Wiegmann &

Shappell, 2003). Precisely, culture is stable and permanant while, climate is dependent and fluctuates in response to change in local variables (Yule, 2003).

iv. The classification category economic pressures instead of social factors has been introduced to the fifth layer of the proposed HFACS-MCTAI model.

The proposed model identifies and classifies various accident risk factors that can affect a marine convoy in ice-covered waters. Risk factors have been used to develop the proposed model are obtained by studying various accident literatures (Chen & Chou, 2012; Danial et al., 2018; Danial, Smith, Khan, et al., 2019a, 2019b; Danial, Smith, Veitch, et al., 2019; B. Khan et al., 2018, 2019; Mazaheri et al., 2015; National Research Council, 1990; Reinach & Viale, 2006; Rothblum, 2000; Sahin & Kum, 2015; Yule, 2003; M. Zhang et al., 2019, 2018). Sections 5.2.1.1 to 5.2.1.5 discuss the above-mentioned risk levels and their classification categories.

5.2.1.1 Unsafe Acts of Operators

Unsafe acts of operators can be classified into two categories: errors and violations (Reason, 1990). Errors are generally characterized as mental or physical activities of individuals/employees that fail to achieve the desired outcome. Violations, on the other hand, are deliberate acts that disregard the rules and regulations regarding safety (Wiegmann & Shappell, 2003). Rasmussen (1982) and Reason (1990) classified errors into decision-based, skill based, and *perceptual* errors, while violations are classified into routine violations and exceptional violations (see Figure 5.2). Decision-based errors are due to the intentional behaviour or actions of an individual that are inadequate or inappropriate in a given situation (Mazaheri et al., 2015;

Wiegmann & Shappell, 2003). Skill-based errors are technical errors that are caused due to improper implementation procedures, inadequate training or low job competency. Perceptual errors result from misunderstandings or misjudgments (M. Zhang et al., 2019). Routine violations are due to frequently ignored rules and instructions, while, exceptional violations occur due to violations of operating procedures. Such violations stem from the inexperience or lack of discipline of operators (Mazaheri et al., 2015; M. Zhang et al., 2019).

5.2.1.1 Preconditions for Unsafe Acts

Wiegmann and Shappell (2003) concluded that approximately 80% of all aviation accidents are due to unsafe acts. The authors also found that the main cause of unsafe acts in aviation accidents is the preconditions for unsafe acts. These preconditions include the environment, condition of operators and personal factors. The same factors are also analyzed as the main causes for unsafe acts in marine accidents (Chen & Chou, 2012; Mazaheri et al., 2015; M. Zhang et al., 2019).

Physical environments, such as harsh weather, can cause unsafe conditions. However, in the proposed HFACS-MCTAI model, we have included ice in the physical environment. Severe states of ice (B. Khan et al., 2018) can cause a major precondition for unsafe acts in maritime accidents. The condition of operators, such as an adverse psychological and physical state due to lack of sleep, and fatigue, can cause a major precondition for unsafe acts in aviation (Wiegmann & Shappell, 2003) as well as in marine accidents (Chen & Chou, 2012; Mazaheri et al., 2015; M. Zhang et al., 2019). Personal factors, such as inadequate communication, coordination, planning and inadequate judgment, which are considered as factors of poor personal readiness, can also play an important role in the precondition for unsafe acts.

The newly introduced classification category, i.e., technical faults, has been proposed as an addition to preconditions for unsafe acts. Technical faults such as mechanical and navigational failures or poor maintenance can cause mental and physical fatigue in the crew (Rothblum, 2000) which can act as major preconditions for unsafe acts in marine accidents.

5.2.1.3 Unsafe Supervision

Unsafe supervision includes inadequate supervision, which is defined as failure to provide proper guidance and training appropriate to the given situation. It also includes failure to identify and control risks during operations (Mazaheri et al., 2015; M. Zhang et al., 2019). The newly introduced classification categories: (1) inadequate planning regarding operations in ice, and (2) failure to recognize a hazard during a convoy, involve inappropriate planning and disregard for the possible risks associated with ice. The fourth classification category of unsafe supervision, i.e., *supervisory violations*, occurs when the supervisor intentionally disregards instructions, guidance, rules, or operating instructions by breaking speed and distance rules (Mazaheri et al., 2015; M. Zhang et al., 2019) that are established according to the given ice conditions.

5.2.1.4 Oraganizational Factors

Wiegmann and Shappell (2003) highlighted the fact that most of the time organizational errors go unnoticed by the safety professionals. They explained that latent failures most often revolve around issues related to resource management, organizational climate, and operational processes.

Zhang *et al.* (2019) in their study also introduced an emergency process to the organizational factors. The proposed HFACS-MCTAI model introduced the class safety culture in place of organizational climate to organizational factors. Resource management and organizational processes remained the same, while emergency preparedness is adopted from Zhang *et al.* (2019).

Resource management involves the allocation and maintenance of organizational assets, such as human resources, monetary assets, equipment and facilities (Wiegmann & Shappell, 2003). Wrongly distributed resources often lead to a safety hazard (M. Zhang et al., 2019). The newly introduced classification category safety culture introduces the broad concept of organizational environments related to appropriate training of crew, using vessels of appropriate ice strength in a convoy, appropriate decisions, proper maintenance, appropriate scheduling, management practices and policies that fecilitate proper risk control options. Any of the these factors which fall outside the acceptable range of values can result in a severe safety breach. Organizational processes involve organizational operations and systems that may adversely affect individuals, supervisory or organizational performances (Mazaheri et al., 2015; M. Zhang et al., 2019). Emergency preparedness is an integral factor of the organizational factors in the proposed HFACS-MCTAI model. It involves emergency response training (Danial et al., 2018; Danial, Smith, Khan, et al., 2019a) of crews and ensures the presence of life jackets, lifeboats, alarms, and visual aids related to emergencies (Danial, Smith, Khan, et al., 2019b; Danial, Smith, Veitch, et al., 2019). The lack of emergency preparedness can cause a severe safety hazard during operations in ice-covered waters.

5.2.1.5 External Factors

Reinach and Viale (2006), proposed an HFACS-RR model in which the authors introduced the fifth layer, external factors to the original model. The authors believed that the identification of accident risk factors should also consider the economy and law policies as supplements in the HFACS (M. Zhang et al., 2019).

(M. Zhang et al., 2019) introduced legislation gaps, administrative oversights, and design flaws to the fifth layer in their model HFACS-SIBCI. The authors explain that legislation gaps involve differences between international and national navigation regulations and policies related to navigation in ice-covered waters. These gaps affect operations under icebreaker escort that may cause poor management or unsafe acts of operators. Administrative oversights involve the negligence of duties by the shipping companies and ship officers. The authors also mentioned design flaws of ships that are usually related to the flawed ability of icebreakers and their assisted ships during icebreaker escorts.

The newly introduced classification category of economic pressures to the layer external factors in the model plays an important role in maritime accidents because tight economic pressures on shipping companies can increase the probability of risk-taking, for instance, making tight schedules which leads taking risks (Rothblum, 2000). It replaces the classification category of social factors in the original HFACS model. Since, social factors are previously present in the layer precondition of unsafe acts—in the function of the condition of operators i.e. fatigue (see Table 5.1) and personal factors i.e. inadequate communication and coordination (see Table 5.1), therefore, in order to remove redundancy in the model, social factors have been replaced with economic pressures in the layer external factors (see Figure 5.2).

5.2.2 Identification and classification of accident risk factors in the HFACS-MCTAI model

In the present section, we first identify accident risk factors for the marine convoy traffic in ice-covered waters on the basis of the five-layer HFACS-MCTAI model (Figure 5.2) proposed in section 5.2.1. Later, we classify risk factors on the basis of 21 classification categories of the proposed HFACS-MCTAI as errors, violations, technical faults, and so on (see Table 5.1).

5.2.2.1 IDENTIFICATION AND CLASSIFICATION OF ACCIDENT RISK FACTORS

Table 5.1 shows the identified risk factor with respective description and classification according to the HFACS-MCTAI model. Risk factors in the proposed study have been classified according to the description of 21 classification categories of the proposed HFACS-MCTAI. These classification categories are described in section 5.2.1. Seven risk factors are identified as unsafe acts of operators (B. Khan et al., 2018; National Research Council, 1990; Rothblum, 2000; M. Zhang et al., 2019). Fifteen risk factors are identified as preconditions of unsafe acts (B. Khan et al., 2018; F. Khan et al., 2014; Rothblum, 2000). Five risk factors are identified as unsafe supervision (B. Khan et al., 2019; M. Zhang et al., 2019), five are identified as

Table 5.1. Description and Classification of accident risk factors during a convoy in ice-covered waters

Risk Levels	Risk Factors	Description	Classification
Unsafe Acts	*Judgment Failures*	Failure to judge unsafe situations, especially related to the maintained distance, speed and emergency situations during a convoy.	*Perceptual error*
	Inadequate Decisions	Decisions based on inadequate information (B. Khan et al., 2018).	*Decision-Based Errors*
	Negligence	Carelessness in taking necessary precautionary actions during emergencies or regular operations.	*Exceptional Violations*
	Loss of Situational Awareness	Being unaware of the relevant circumstances, especially in case of emergencies.	*Perceptual Error*
	Inadequate General Technical Knowledge	Lack of knowledge of the proper use of technology, for instance, radar (Rothblum, 2000).	*Skill-based Error*
	Improper Lookouts	Inadequate watch keeping in various locations and duties aboard the ship, for example, bridge and engine room.	*Exceptional Violations*
	Deficiency of Crew Attention	The inadequate timely response of a crew in emergencies or during regular operations.	*Skill-Based Error*
Preconditions for Unsafe Acts	*Extremely Low Temperatures*	In higher latitudes, extremely low temperatures can cause fog or snow or sometimes vessel icing that can cause a ship to collide with another ship/object or lose stability during navigation.	*Physical Environment, Weather*
	Fog	Can cause poor visibility.	*Physical Environment, Weather*
	Darkness	In higher latitudes, long polar nights can affect visibility during navigation.	*Physical Environment, Weather*
	Poor Visibility	Poor visibility due to fog and snow can affect radar visibility.	*Physical Environment, Weather*
	Blowing Snow	Hazardous natural environmental phenomena	*Physical Environment, Weather*
	Ice	Hazardous for ship navigation	*Physical Environment, Ice*

Risk Levels	Risk Factors	Description	Classification
	Types of Ice	Presence of new ice, thick first-year ice, old ice, ice floes, fast ice, level ice, drift ice, and deforming ice is significantly hazardous for navigation in ice-covered waters (ABS advisory, 2009; Canadian Coast Guard, 2012b).	*Physical Environment, Ice*
	Ice Concentration	The relative amount of area covered by ice. It is typically reported in terms of percentage. 0% means there is no ice, while 100% means the region is completely covered by ice.	*Physical Environment, Ice*
	Ice Strength	The ice thickness and types account for ice strengthening in the sea and are considered the most common factors of accidents (B. Khan et al., 2018).	*Physical Environment, Ice*
	Ice Drift	Drifting ice is a major threat to vessel operations in higher latitudes.	*Physical Environment, Ice*
	Inadequate Communication and Coordination	Inadequate communication and coordination between crew members of a ship, crew members and the master of a ship, ship to ship during a convoy, ship to icebreaker during a convoy, and ship to Vessel Traffic Service (VTS) onboard during a convoy.	*Personal Factors, Coordination and Communications*
	Poor Maintenance	Crew reductions can result in the neglect of essential maintenance (National Research Council, 1990).	*Technical Faults*
	Mechanical Failures	Engine failure of icebreaker or any other ship in a convoy, steering gear failure, anti-collision system failure, failure of the communication equipment (M. Zhang et al., 2019) between the icebreaker and any of the assisted ships in a convoy.	*Technical Faults*
	Navigational Failures	Inadequate availability of precise, written, and comprehensible operational procedures (Rothblum, 2000), ice and navigational charts. Ineffectiveness of radar and radio communication, and inadequate navigational searchlights (B. Khan et al., 2018).	*Technical Faults*
	Fatigue	Poor maintenance, navigational and mechanical failures, lack of sleep, and overload can cause fatigue.	*Condition of Operators, Adverse Psychological States*
Unsafe Supervision	*Failure to maintain a safe speed in Ice*	The speed of an icebreaker or the ships in a convoy is higher than the recommended standards.	*Failure to recognize a*

Risk Levels	Risk Factors	Description	Classification
			hazard during a convoy
	Failure to maintain a safe distance between 2 ships during a convoy	The distance between the two ships in a convoy is shorter than the recommended standards causing an unsafe collision risk between two ships in a convoy.	*Inadequate planning regarding Operation in Ice*
	Failure to maintain a safe distance between an icebreaker and a leading ship of a convoy	The distance between the icebreaker and a leading ship of a convoy is shorter than the recommended standards causing an unsafe distance between the icebreaker and a leading ship of a convoy.	*Inadequate planning regarding Operation in Ice*
	Failure to continue a safe operation in Ice	The improper route design makes it hard or dangerous to continue safe operations in ice.	*Inadequate Supervision*
	Inadequate route selection	Improper route selection for a convoy in ice-covered waters can cause a ship-ice or icebreaker-ice collision during a convoy (B. Khan et al., 2018).	*Inadequate Supervision*
Organizational Factors	*Management practices*	Management practices such as maintenance, training schedule, and crew reduction (National Research Council, 1990) can cause a severe safety hazard if not handled appropriately.	*Safety Culture*
	Crew Reduction	Crew reduction can cause the crew to be overloaded; this can result in the lack of attention of crew aboard that negatively affects the safety of the ship or its crew (National Research Council, 1990).	*Resource Management*
	Crew Overloaded	Crew reduction can cause the crew to be overloaded; this can result in the lack of attention of crew aboard that negatively affects the safety of the ship or its crew (National Research Council, 1990).	*Resource Management*
	Lack of Training	Improper management practices involve gaps in training	*Safety Culture*
	Maintenance	Improper management practices involve improper *maintenance*	*Safety Culture*
	Schedules	Faulty management practices and policies encourage risk-taking i.e. to meet the schedules at all costs (Rothblum, 2000).	*Safety Culture*
	Risk Taking	Negative attitudes of organization towards safety, and faulty management practices and policies encourage *Risk Taking* i.e. to meet the schedules at all costs (Rothblum, 2000).	*Safety Culture*

Risk Levels	Risk Factors	Description	Classification
	Lack of Emergency Preparedness	Lack of emergency training in the icebreaker and its assisted ships in a convoy (M. Zhang et al., 2019).	*Emergency Preparedness*
External Factors	*Economic Pressures*	Tight economic pressures can cause unsafe situations during operations.	*Economic Factors*
	Faulty Company Policies and Standards	Faulty management practices and policies encourage risk-taking i.e. to meet the schedules at all costs (Rothblum, 2000).	*Administrative Oversights*
	Design Flaws	(1) Icebreaker or any other ship in a convoy does not have enough capacity to cope-up with the existing ice environment in the region, (2) icebreaker or any other assisted ship in a convoy has a lack of engine power, and (3) no combined ship collision avoidance rule exists during icebreaker assistance, which can result in risk of collision during a convoy (M. Zhang et al., 2019).	*Design Flaws*

organizational factors (National Research Council, 1990; M. Zhang et al., 2019), and three risk factors are identified as external factors (Rothblum, 2000) respectively (see Table 5.1).

5.2.3 Development of the cause-consequence relationship among the accident risk factors

This section explains how the risk factors considered in the HFACS-MCTAI model per layer contribute to a consequence or effect. A BN model (Figure 5.3) for unsafe acts considers the relevant risk factors as input nodes and estimates the probability of occurrence of unsafe acts as a function of the risk factors. Similarly, BN models for precondition of unsafe acts, unsafe supervision, organizational factors, and external factors have been constructed and presented in Figures 5.4-5.7 respectively. Interested readers should consult (Chen & Chou, 2012; Islam et al., 2018b; B. Khan et al., 2018, 2019; F. Khan et al., 2014; Mazaheri et al., 2015; National Research Council, 1990; Rothblum, 2000; Sahin & Kum, 2015; M. Zhang et al., 2019) to understand the relationships among the risk factors considered in the BNs. Some of the prior probabilities have been taken from earlier studies (B. Khan et al., 2019; F. Khan et al., 2014; Rothblum, 2000). The software package GiNIe 2.2 (BayesFusion, 2018) is used for the construction of the BNs.

5.2.4 Estimation of accident probabilities during a convoy in ice-covered waters – winter navigation of the marine convoy traffic on the St. Lawrence seaway

The St. Lawrence Seaway (Figure 5.8) allows vessels to travel from the Atlantic Ocean to the great lakes of North America. The seaway named Saint Lawrence River, flows from Lake Ontario to the Gulf of St. Lawrence, Atlantic ocean. The river is officially extended from Montreal, Quebec to Lake Erie. The navigation season on the river extends from late March to late December. Ice begins to form in the river during the first half of December between Montreal and Quebec city. The combination of river currents and winds produces new ice to grow and spread along the south shore of the river. Ice in the region, typically grows to 20 to 60 centimeters in winters, while ridging, rafting, and hammocking can significantly increase these thicknesses. Ice floes in the region are thick and large (up to eight km or more), they are uneven and discolored and are easy to identify. Masters are advised to avoid them, as they are the major hazards to navigation in the region (Canadian Coast Guard, 2012a).

The shipping channels are mostly congested by ice in winter, this is due to the ice removed from the banks to which it is attached (Canadian Coast Guard, 2012a). For such reasons, the icebreaker assistance operation is sometimes necessary to continue maneuvers on the river.

Here we assume that an icebreaker assistance convoy operation is comprised of five vessels (oil tankers and bulk carriers) transiting the St. Lawrence Seaway. First, we estimate the accident probabilities of unsafe acts, preconditions of unsafe acts, unsafe supervision, organizational factors, and external factors that are earlier identified and classified on the basis of the proposed HFACS-MCTAI (see section 5.2.1), and then calculate the critical density of the traffic flow in the channel (see Tables 5.2 and 5.3, and Figures 5.9 and 5.10).

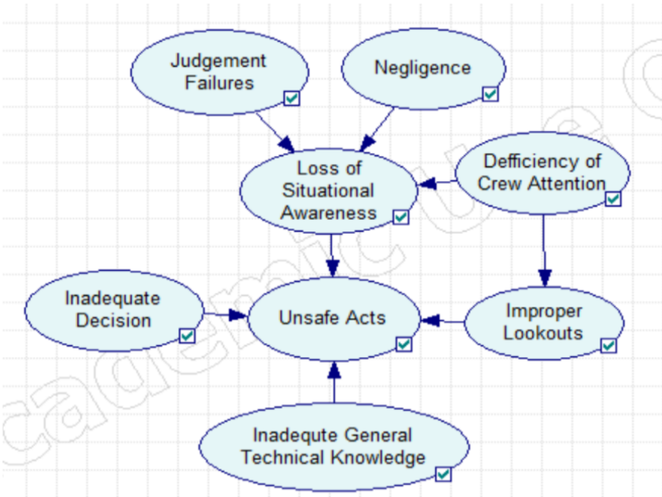

Figure 5.3. Cause-Consequence relationship among the risk factors for *Unsafe Acts*.

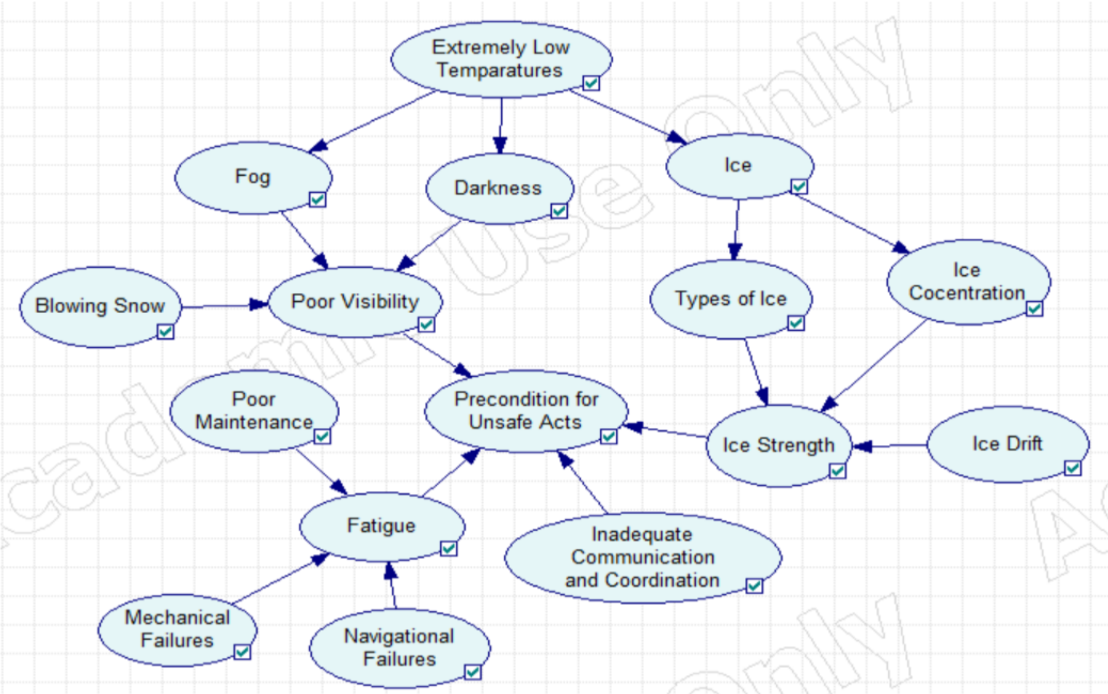

Figure 5.4. Cause-Consequence relationship among the risk factors for *Precondition for Unsafe Acts*.

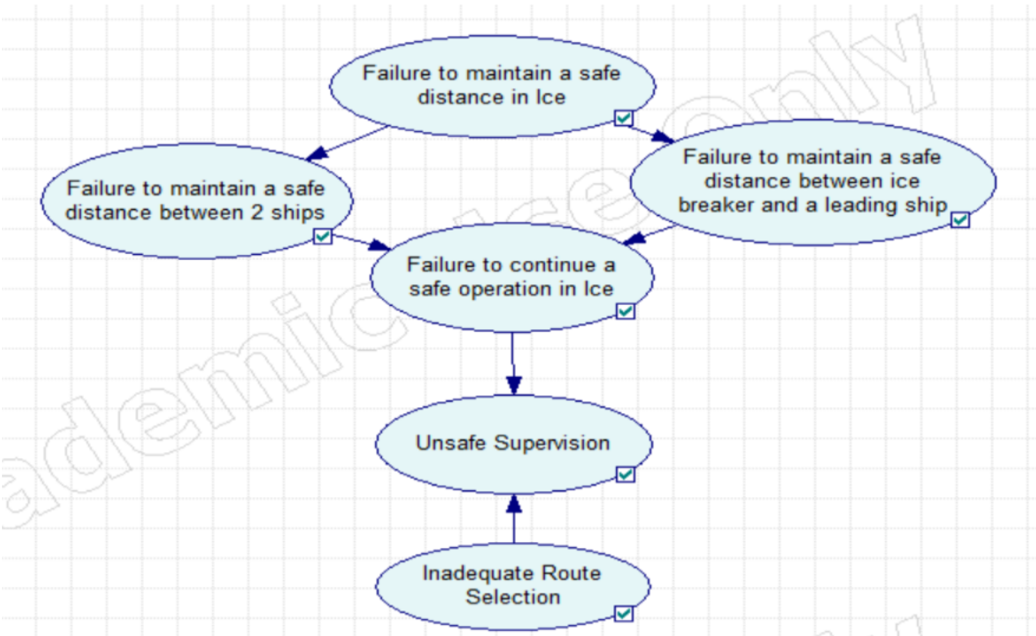

Figure 5.5. Cause-Consequence relationship among the risk factors for *Unsafe Supervision*.

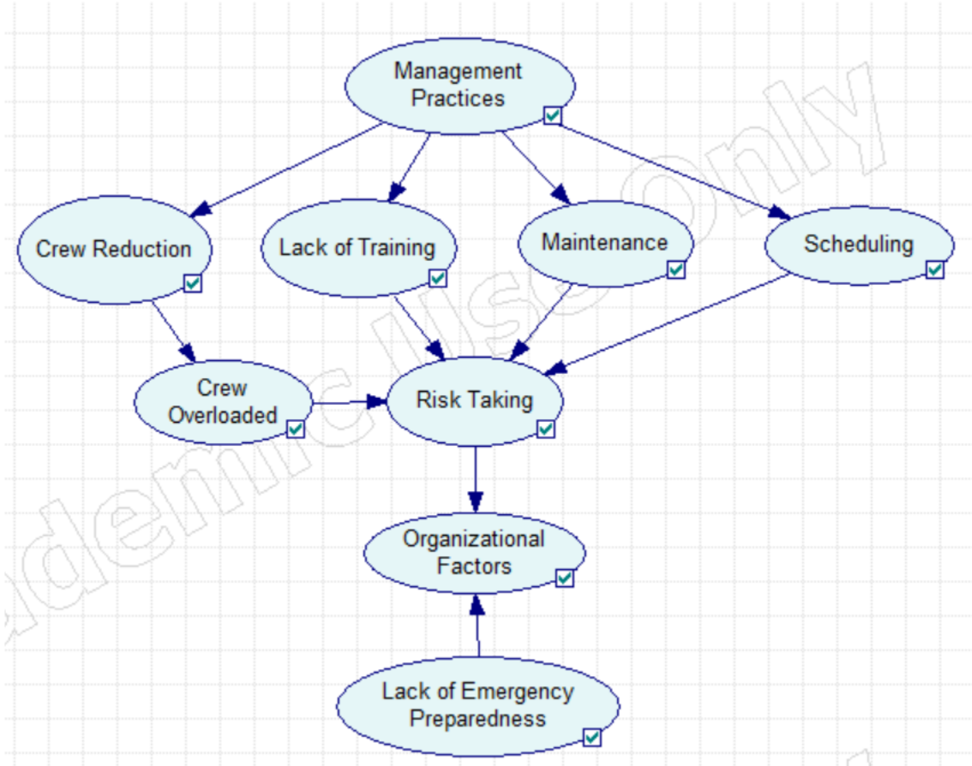

Figure 5.6. Cause-Consequence relationship between the risk factors for *Organizational Factors*.

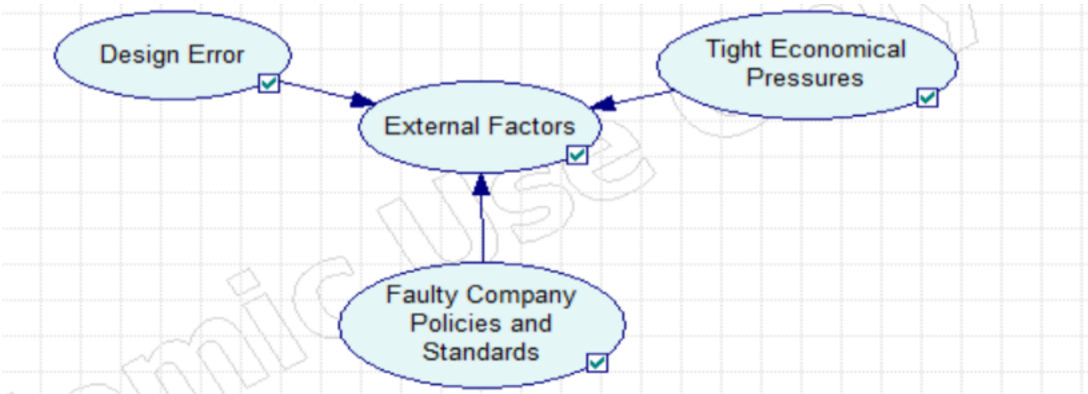

Figure 5.7. Cause-Consequence relationship among the risk factors for *External Factors*.

Table 5.2. Estimated accident probabilities of marine convoy traffic on the St. Lawrence Seaway

Risk Factors	Estimated Probabilities
Unsafe Acts	0.10
Preconditions for Unsafe Acts	0.11
Unsafe Supervision	0.02
Organizational Factors	0.01
External Factors	0.07
Ship-ice Collision	0.02
Collision between two ships	0.04
Collision between an icebreaker and the leading ship of a convoy	0.04

Table 5.3. Estimation of critical densities $\rho_{critical\ densities}$ of marine convoy traffic on the St. Lawrence seaway with respect to the varied maximum velocities v_{max} and deceleration probabilities $p_{deceleration}$.

Maximum Velocity v_{max} (ship/timestep)	Deceleration Probability $p_{deceleration}$	Critical Density $\rho_{critical\ density}$ (ship/site)
3	0.01	0.25
3	0.10	0.22
3	0.30	0.18
5	0.02	0.18
5	0.24	0.12
5	0.30	0.10

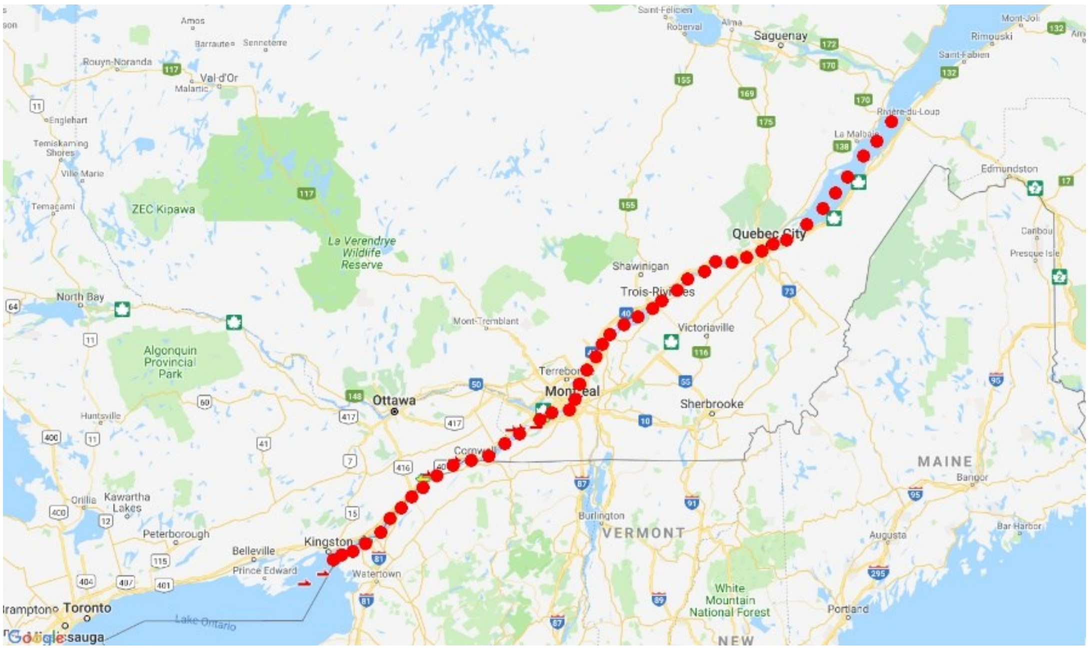

Figure 5.8. St. Lawrence Seaway (Source: Google maps).

5.2.4.1 Probability Estimation

Table 5.2 shows the estimated accident probabilities of unsafe acts, preconditions for unsafe acts, unsafe supervision, organizational factors, and external factors for marine convoy traffic on the St. Lawrence Seaway that have been calculated from Figures 5.3 to 5.7. Since, in the present study, we have attempted to model human errors and the quantification of human errors in maritime risk assessment perspective is relatively difficult. For such reason, some of the prior values of human errors that have been used in the study are based on assumptions, while some have been taken from the earlier studies (B. Khan et al., 2018, 2019; F. Khan et al., 2014; Rothblum, 2000). Therefore, the magnitude of the estimated posterior probabilities presented in Table 5.2 are significantly variable. In the BN of unsafe acts, all risk factors are Boolean variables that take values from the set {Yes, No}.

In the BN for preconditions of unsafe acts, the node *ice strength* takes values from the set {High, Medium, Low}, the node types of *ice* takes values from the set {New Ice (NI), Fast Ice (FI), Ice Floes (IF), Ice Ridge (IR)}, however, the remaining nodes are all Boolean. BN for unsafe supervision contains all Boolean nodes, and takes values from the set {Yes, No}. The node *Management Practices* in the BN for organizational factors takes values from the set {Inappropriate, Appropriate}, the node *Maintenance* takes values from the set {Proper, Improper}, the node *Scheduling* takes values from the set {Tight, Relaxing}, and the node *Organizational factors* takes values from the set {Present, Absent}. The remaining nodes take values from the set {Yes, No}. The node *External Factors* in the BN of External Factors takes values from the set

{Present, Absent}, while, all other nodes of the BN are Boolean, taking values from the set {Yes, No}.

5.2.4.2 Critical Density Estimation

The present section adopts the Cellular Automata (CA) technique called the Nagel and Schreckenberg (NaSch) model (1992) for critical density estimation. NaSch model is one of the most widely used cellular automata theory based traffic model. This model is selected in the present study due to its relevance to simulate covey traffic scenarios.

The primary purpose of using NaSch model is to (a) estimate the critical density of the convoy traffic to avoid sudden traffic jams and collisions in ice-covered waters, (b) simulate scenarios of safe distance between two ships of the convoy and between the leading ship of a convoy and icebreaker, and (c) to integrate HFACS-MCTAI which helps to study the effects of unsafe acts, preconditions for unsafe acts, unsafe supervision, organizational factors, and external factors on critical density, deceleration probability, the maximum velocity of the system and the sudden traffic jam during a convoy in ice-covered waters. Wright (2013), in his article describes the global density ρ and global flow $J(\rho)$. The NaSch model, with a little updating in the rules, can also be used for maritime traffic flow (B. Khan et al., 2019; Qi et al., 2017a).

This section presents the $\rho_{critical\ density}$ estimation of a marine convoy traffic flow on the St. Lawrence Seaway using an updated NaSch model (B. Khan et al., 2019). For such a purpose, we take a shipping channel in the St. Lawrence Seaway of the length of 45,120m and divide it into 200 equal cells (i.e. L =200 cells); each cell has

L = 225.6m. We use 200 iterations, i.e., $T_e = 200$, where each T_e is approximately 1 sec (an approximation of the response time of a ship operator). Values of v_{max} have been selected randomly as 3 and 5, and values of $p_{deceleration}$ have been selected randomly from the range 0.01-0.30. The reason for doing so is to see the behavior of the flow at random values of v_{max} and $p_{deceleration}$ in the system. The results of the simulation (Figure 5.9) show that the $\rho_{critical\ density}$ of the flow decreases with the increasing values of v_{max} and $p_{deceleration}$ respectively (see the values of $\rho_{critical\ density}$ with respect to v_{max} and $p_{deceleration}$ in Table 5.3). Increasing v_{max} and $p_{deceleration}$ cause the maximum flow and mean velocity of the system to collapse at lower densities, leading to sudden traffic jams and possible collision accidents in the region. In Figure 5.9, the value pointed to by the arrows are the estimated critical densities of the marine convoy traffic on the St. Lawrence Seaway.

5.2.5 Integrated Accident Model (IAM) for Marine Convoy Traffic in Ice-covered Waters

Since $p_{deceleration}$ is a stochastic component introduced in the NaSch model by the process of randomization, it induces a non-deterministic motion of vehicles due to operators' behavior (Nagel & Schreckenberg, 1992; Wright, 2013). Khan *et al.* (2019) proposed the updated version of the NaSch model in which, including the process of randomization, all the rules of road traffic are updated with respect to the marine convoy traffic in ice-covered waters. Here we integrate the HFACS-MCTAI model with the updated NaSch model. The model is also extended to observe the effects of the risk levels reported in Table 5.1 on v_{max}, $p_{deceleration}$, $\rho_{critical\ density}$, and sudden traffic jam during a convoy in ice-covered waters. The model estimates the accident probabilities of collision between two ships, ship-ice collision and collision between an icebreaker and the leading ship in a convoy. The integration takes place through BN (Figure 5.10). The resulting model is called the Integrated Accident Model (IAM) for Marine Convoy Traffic in Ice-covered Waters.

The nodes in the model are Boolean. The nodes $p_{deceleration,}v_{max}$, and $\rho_{critical\ density}$ take values from the set {High, Low}, while the nodes sudden traffic jam, collision between two ships, ship-ice collision, and collision between an icebreaker and the leading ship in a convoy take values from the set {Yes, No}respectively.

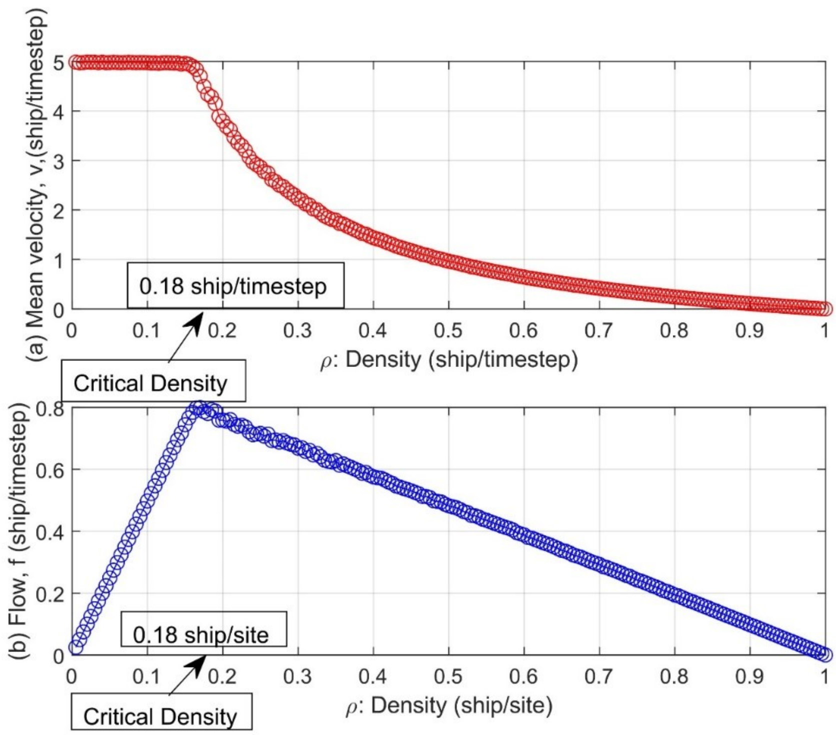

Figure 5.9. Simulation results of marine convoy traffic on the St. Lawrence Seaway using updated NaSch model with $p_{deceleration} = 0.02$, $v_{max} = 5$, $n = 200$, and $T_e = 200$ (a) Mean velocity, v vs Density, ρ, (b) A fundamental density-flow diagram.

5.3 Results and Discussion

The hypothetical case study illustrates that precondition of unsafe acts plays the most frequent role in the accidents during a convoy on the St. Lawrence Seaway, while unsafe acts stands second, followed by external factors, unsafe supervision, and organizational factors (Table 5.2). The results agree with the results of (M. Zhang et al., 2019). Table 5.3 presents the values estimated through the updated NaSch model for the critical density of a marine convoy on the St. Lawrence Seaway. The accident probabilities of ship-ice collision, collision between two ships in a convoy, and collision between an icebreaker and the leading ship of a convoy, that are computed by using the IAM model are also given in Table 5.2.

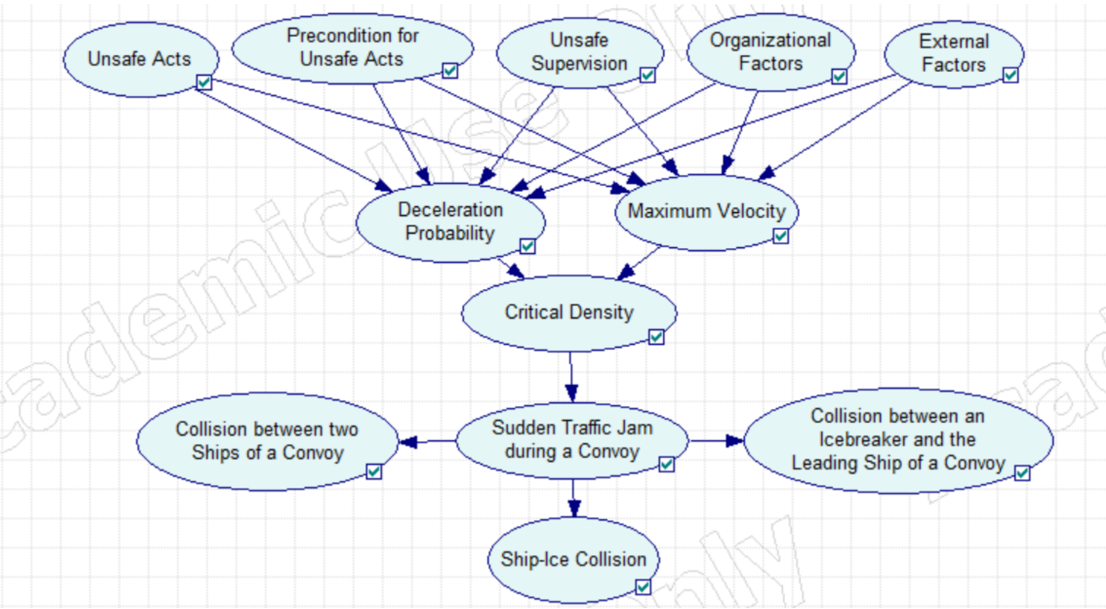

Figure 5.10. The IAM model.

Table 5.4. Percent contribution of the accident risk factors on *Unsafe Acts of Operators* during a convoy on the St. Lawrence Seaway

Ranking	Risk factors in BN of *Unsafe Acts*	Effect of the risk factors on *Unsafe Acts* (% contribution sensitivity analysis)
1	*Inadequate General Technical Knowledge*	27.00
2	*Inadequate Decisions*	26.60
3	*Improper Lookouts*	24.40
4	*Deficiency of Crew Attention*	14.10
5	*Judgment Failure*	7.400
6	*Negligence*	7.300
7	*Loss of Situational Awareness*	3.300

Table 5.5. Percentage of contribution of the risk factors on *Precondition for Unsafe Acts* during a convoy on the St. Lawrence Seaway

Ranking	*Risk factors*	Effect risk factors on *Precondition for Unsafe Acts* (Percent contribution sensitivity analysis)
1	*Ice Concentration*	25.60
2	*Extreme Low Temperatures*	23.60
3	*Ice*	22.50
4	*Fatigue*	21.30
5	*Blowing Snow*	14.70
6	*Ice Drift*	14.60
7	*Darkness*	14.00
8	*Fog*	13.90
9	*Inadequate Communication and Coordination*	11.20
10	*Poor Maintenance, Mechanical Failure, Navigational Failure*	5.500
11	*Ice Strength*	3.700

Table 5.6. Percentage of contribution of the risk factors on *Unsafe Supervision* during a convoy on the St. Lawrence Seaway

Ranking	Risk factors	Effect of the risk factors on *Unsafe Supervision* (Percent contribution sensitivity analysis)
1	*Inadequate Route Selection*	25.70
2	*Failure to continue a safe Operation in Ice*	24.80
3	*Failure to continue a safe distance in Ice*	13.40
4	*Failure to maintain a safe distance between two ships and failure to maintain a safe distance between an icebreaker and a leading ship of a convoy*	6.300

Table 5.7. Percentage of contribution of the risk factors on *Organizational Factors* during a convoy on the St. Lawrence Seaway

Ranking	Risk factors	Effect of the risk factors on *Organizational Factors* (% contribution sensitivity analysis)
1	*Lack of Emergency Preparedness*	25.70
2	*Risk Taking*	23.40
3	*Management Practices*	6.900
4	*Crew Overloaded*	6.100
5	*Lack of Training, Maintenance,* and *Scheduling*	5.700

Table 5.8. Percentage of contribution of the risk factors on *Extra Factors* during a convoy on the St. Lawrence Seaway

Ranking	Risk factors	Effect of the risk factors on *Extra Factors* (% contribution sensitivity analysis)
1	*Design Error*	30.30
2	*Faulty Company Policies and Standards*	28.90
3	*Tight Economic Pressures*	27.70

Table 5.9. Failure probabilities of the nodes and their effect on accident probabilities during a convoy on the St. Lawrence Seaway

Ranking	Nodes	Failure Probabilities	Effect of the nodes on accident probabilities (Percentage of contribution sensitivity analysis)
1	*Sudden Traffic Jam*	0.06	65.90
2	*Critical Density*	0.06 (Low)	64.60
3	*Deceleration Probability*	0.03 (High)	37.80
3	*Maximum Velocity*	0.05 (High)	37.80
4	*Organizational Factors*	0.01 (Present)	13.20
5	*Unsafe Supervision*	0.02	12.90
5	*External Factors*	0.07	12.90
6	*Unsafe Acts*	0.10	12.80
6	*Precondition of Unsafe Acts*	0.11	12.80

5.3.1 Sensitivity Analysis

Sensitivity analysis is performed to determine the percentage contribution of accident risk factors for those listed in the risk levels of unsafe acts, precondition of unsafe acts, unsafe supervision, organizational factors, and external factors (see Tables 5.4 to 5.8). This section also shows the failure probabilities of unsafe acts, precondition for unsafe acts, unsafe supervision, organizational factors, external factors, deceleration probability, maximum velocity, critical density, sudden traffic jam, and their contribution percentage to the accident probabilities in a convoy on the St. Lawrence Seaway (see Table 5.9).

Table 5.4 shows that inadequate general technical knowledge, inadequate decision, improper lookouts, and deficiency of crew attention have the greatest impact on unsafe acts of operators. Table 5.5 shows that ice concentration, extreme low temperatures, ice, fatigue, blowing snow, ice drift, darkness, fog, and inadequate communication influence the preconditions for unsafe acts during a convoy. However, 25% contribution each of poor maintenance, mechanical failures, and navigational failures can cause fatigue during a convoy.

Table 5.6 shows that inadequate route selection, failure to continue a safe operation in ice, and failure to maintain a safe distance in ice have played the greatest role in unsafe supervision during a convoy. Table 5.7 shows that lack of emergency preparedness and risk taking have diminished the role of organizational factors during a convoy, while around 27% contribution of management practices, 24% contribution of crew overloaded, 22% contribution of lack of training, maintenance and scheduling and about 17% contribution of crew reduction in risk taking make the situation worse during the convoying. Table 5.8 shows that design error, faulty company policies and standards, and tight economic pressures have a major impact on *External Factors* during a convoy on the St. Lawrence Seaway.

Table 5.9 shows the failure probabilities of the nodes and their effects on accident probabilities. Table 5.9 also shows that sudden traffic jam, critical density, deceleration probability, and maximum velocity have a major influence on accident probabilities in convoying on the St. Lawrence Seaway. Moreover, the analysis shows that around 19% of the organizational factors, 18% contribution of unsafe supervision and external factors, and 18% contribution of unsafe acts and precondition of unsafe acts in deceleration probability, maximum velocity, critical density, and sudden traffic jam can further increase the accident probabilities during the convoying.

5.4 Conclusions

This study proposed two models, both of which have been applied to a convoy navigating through St. Lawrence Seaway. The first model, HFACS-MCTAI, is used to identify and classify the contributing risk factors during a convoy in ice-covered waters. In the present study, we have also developed the cause-consequence relationships between the risk factors of the model. The relationships have been developed through a BN. The main purpose of developing the cause-consequence relation is to estimate the accident probabilities of the risk factors, and also to investigate the most frequently occurring risk factor in a convoy. The model, along with the BN of risk factors (which developed a cause-consequence relationship), when applied on the St. Lawrence Seaway, demonstrated that preconditions for unsafe acts are the most frequent contributing risk factor. This conclusion is based on the highest probability of occurrence (see Table 5.2) during a convoy on the St. Lawrence Seaway followed by unsafe acts, external factors, unsafe supervision, and organizational factors respectively.

The second model is the IAM model. This model is an extension of the earlier model proposed by the authors in the work of (B. Khan et al., 2019). The extension is conceived in terms of integration of an updated NaSch model with an HFACS-MCTAI model. This integrated model considers an operator's behaviour and links it with the occurrence of various risk factors during a convoy, such as the physical environment, technical faults, organizational, and external factors identified and classified through HFACS-MCTAI. The IAM model is innovative: it aims to estimate the effects of unsafe acts, preconditions for unsafe acts, unsafe supervision, organizational factors, and external factors on maximum velocity, deceleration probability, critical density, and sudden traffic jam during a convoy. IAM also estimates the accident probabilities of ship-ice collision, collision between two ships, and collision between an icebreaker and the leading ship of a convoy in ice-covered waters.

The present study estimated the critical density of a convoy needed to avoid sudden jams and collisions during a convoy on the St. Lawrence Seaway. The study also demonstrated that sudden traffic jam, critical density, deceleration probability, and maximum velocity greatly influence the accident probabilities.

The proposed method is used to identify the contributing risk factors that can help in preventing accidents during a convoy in ice-covered waters. The methodology is also useful in route identification and selection during a convoy. This study introduces two new risk factors: crew reduction, and crew overloaded, in the risk layer of organizational factors. These risk factors do not directly influence the accident probability of organizational factors. However, a small increase in these factors greatly influences the risk of an accident. For example, based on the sensitivity analysis, it is determined that about a 17% contribution of crew reduction and about a 24% of contribution of crew overloaded increase the contribution of risk taking by an amount of approximately 93% in the overall risk of accidents. The accident probabilities obtained through the integrated model will be helpful in decision making concerning safe operations during a convoy in ice-covered waters. To obtain reliable results, it is necessary to have reliable prior beliefs for BNs. 1n the present study, we have attempted to model human errors. The quantification of human error is a challenging job, especially in a maritime risk assessment context. Therefore, some of the values that have been used in the study are based on assumptions. The collection of near-miss data and human error data similar to that collected in the aviation domain would be helpful in generating reliable prior beliefs in future. Nevertheless, the proposed models can be useful in developing a collision monitoring system that provides a real-time estimate of collision probabilities.

In the present study, the validity of the proposed models has checked on the St. Lawrence Seaway Sea. However, with the little modification in the changing sea-ice and weather related conditions, the model can be applied to the other routes of the Arctic waters, for instance, the route from Murmansk to China, Vilkitskii strait, and the routes of Barents Sea.

The present study can also be extended by using the evidential reasoning method and fuzzy set theory in combination with the proposed model. This would help to reduce data uncertainty.

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Chapter 6

Conclusions & Recommendations

6.1 Conclusions

This research presents conceptual models for understanding, examining, and applying the requirements demanded in the content of existing accident modeling standards in the maritime domain. Arctic navigation has many complexities and discrepancies than regular navigation because of its icy waters, cold temperatures, snow-storms, and low visibility due to fog, blowing snow, and long polar nights. One of the main contributions of this thesis is the identification of the risk factors related to Arctic navigation and develop the probabilistic-framework tools to assess the risk of ship-ice collision during the independent navigation and the risk of ship-ice/ship/icebreaker collision during a convoy in the region. BN technique has been generally used in this thesis to model ship-ice and ship-ship/icebreaker collisions. The main purpose of these models is not only estimating the collision probabilities but also to determine the causal relationships between the risk factors and their influence on collision probability. The key benefits of using BN models are, (1) it makes predictions with incomplete data, (2) combine subjective beliefs with objective data, (3) update previous beliefs in the light of new pieces of evidence, (4) Both forward and backward inferences are possible, (5) elicitation of probabilities and explaining model results are easier and simpler, (6) it can combine the experimental data with subjective beliefs, and (7) its ability to interconnect arguments effectively. All the above mentioned benefits of BN modeling, all together with the specific quantification of uncertainties make BNs an effective and compelling solution for many types of risk assessment problems.

Besides, the current thesis also presents the updated Nagel-Schrekenberg (NaSch) model and the HFACS-Marine Convoy Traffic in Ice-covered waters (HFACS-MCTAI) in conjunction with BN. To check the model sensitivity and the sensitivity of model parameters (associated risk factors), sensitivity, and uncertainty analyses have also been performed in this study.

The present research is divided into two parts: (1) risk-based collision modeling for the independent navigation and (2) risk-based collision modeling for the convoy traffic in the Arctic. For the independent navigation, we have merely used BN techniques to model the risk-based scenarios of the ship-ice collision, however, for the convoy traffic, we have used the updated NaSch and HFACS-MCTAI models with BNs to model the risk-based scenarios of the ship- ice/ship/icebreaker collisions.

Initially, for the independent navigation, we have identified certain risk factors and constitute OOBN models namely, (1) Ship Navigational System states, (2) Ship Operational System states, (3) Ice States, (4) the Weather States, and (6) Human error. Later, we integrate all such models to construct a ship-ice collision model to estimate the collision probability. While the main purpose to use the OOBN methodology in the present research is to decompose a large network into small components so that it is easy to comprehend the visual representation of risk factors. Also, OOBNs are advantageous in such a way that they simplify the marine accident modeling through hierarchical and component-by-component analysis. The OOBN models can be expanded for new components without affecting the existing components in the models, they are also useful to identify the root causes of an accident and analyze them individually.

The OOBN/BN does not account for time dependence; therefore, a study has been extended by employing the DBN technique to the risk-based scenario of ship-ice collision. The main purpose of generating the DBN model of the ship-ice collision scenario is to support the operational and navigational decisions while navigating on the Arctic waters in connection with time. Such time-oriented decisions are more vigorous in reducing collision risks in the region. DBN methodology in maritime risk analysis studies is beneficial because it reduces the computational complexities by making the risk factors time-dependent, the methodology also provides support to decision making where data is not clear.

For convoy traffic, this research presents an updated NaSch model, the CA-based technique in conjunction with BN. The NaSch model provides a new perspective on the dynamics of Arctic navigation. The model simplifies maritime accident modeling by developing a practical understanding of the role of macroscopic properties i.e. critical density, deceleration probability, and maximum velocity of the traffic flow in maritime convoys to avoid collisions and sudden traffic jams. The model presents the concepts of randomization and ship domain in a convoy. The model is useful in estimating the critical densities, while the model simulation shows that lower values of critical density result in sudden traffic jams and collisions, however, higher values of critical densities avoid sudden jams and collisions in the convoy. The model relates the non-deterministic motion of vehicles in a convoy with operators' behavior. The present research also identifies the main factors for convoy safety; (1) maintaining a safe distance between two ships, (2) maintain a safe speed in ice, (3) safe operations in ice, and (4) maintain a safe distance between an icebreaker and the leading ship of a convoy. The updated NaSch model is integrated with BN to see the effect of macroscopic properties on the main factors for convoy safety and estimate the collision probability in a convoy. The research also shows the influence of macroscopic properties of the convoy on collision probability.

The research further extends and presents the Integrated Accident Model (IAM) for marine convoy traffic in ice-covered waters. For such purpose, HFACS-MCTAI has been proposed in which various contributory accidental risk factors have been identified and classified as unsafe acts, the precondition for unsafe acts, unsafe supervision, organizational factors, and external factors, respectively. The study proposes the HFACS-MCTAI model based on some changes made in the existing classification categories of the original HFACS model. Later the cause-consequence relationship has also been developed among the risk factors that have been identified and classified through the HFACS-MCTAI model. The main purpose of developing the cause-consequence relationship is to estimate the accident probabilities of the risk factors and also to estimate the most frequently occurring risk factor in a convoy. Further, the HFACS-MCTAI model is combined with an updated NaSch model through BN to develop the IAM model. The IAM model is innovative, its main purpose is to extend the concept of an operator’s behavior in a convoy by adding the knowledge of various risk factors that are identified and classified through the HFACS-MCTAI model. Further, the model is also used to observe the effects of unsafe acts, the precondition for unsafe acts, unsafe supervision, organizational factors, and external factors on deceleration probability, maximum velocity, critical density, and sudden traffic jam in a convoy navigating in ice-covered waters. The model is also used to estimate the collision probability between the two ships, ship and ice, and the icebreaker and the leading ship of a convoy.

Nevertheless, the present study reveals that the human error such as decision-based on inadequate information, inadequate communication, and fatigue, the presence of high/moderate ice strength, poor visibility, and the high speed of the vessel are the most critical risk factors that are greatly responsible for ship-ice collision during the independent navigation in Arctic waters. The study also reveals that the lower critical densities with high deceleration probabilities and maximum velocities are wholly responsible for the failures of the main factors of convoy safety. A slight change in the values of macroscopic properties can significantly affect the factors and all these factors are equally sensitive for collision in a convoy. It is also observed in the study that the high densities along with the lower deceleration probabilities and velocities prevent the factors from failure and avoid sudden jams and collisions in a convoy. It is also revealed through this study that preconditions for unsafe acts are the most contributing risk factor occurring in a convoy, followed by unsafe acts, external factors, unsafe supervision, and organizational factors, respectively. The study also suggests that the estimation of the critical density of a convoy is always necessary to avoid sudden jams and collisions. Further, this study also introduces two new risk factors; (1) crew reduction, and (2) crew overloaded that do not directly influence the collision probability, however, a small increase in these factors greatly influence the risk of collision in a convoy.

6.2 Recommendations and future work

The probabilities obtained through the proposed models can be used in decision making concerning safe operations in ice, for instance, maneuvering, route selection, towing, escorting, etc. The estimated probabilities are also helpful in the selection of a safe speed while navigating in Arctic waters. Also, the probabilities help investigate frequently occurring risk factors during independent navigation as well as in the convoy traffic. In this research, the proposed models are theoretical and conceptual, however, they can be useful in developing a collision monitoring system that provides a real time-estimate of collision probability in the future that could help avoid ship-ice/ship/icebreaker collisions in the region.

The estimated probabilities that are obtained through the integrated models can be useful in estimating critical densities, selection of appropriate deceleration probabilities, maintaining a safe speed, maintaining a safe distance between the icebreaker and the leading ship of a convoy, and maintaining a safe speed between the two ships of a convoy. In the future, the present study can be extended by calculating the ship domain i.e. the minimum safe distance between two ships according to the prevailing ice conditions in the waterways, harsh weather, and operational and navigational states of ships in convoys.

In the present study, we have attempted to model human errors through BN, NaSch, and HFACS-MCTAI methodologies, though, the quantification of human error is a challenging job in a maritime risk assessment context. In the future, maritime authorities must collect near-miss and human error data similar to that collected in the aviation domain to reduce the uncertainty component in maritime risk modeling. Uncertainty is an unavoidable component in any risk assessment procedure and the lack of data aggravates the difficulties. To reduce the uncertainties to some extent, the present study can also be extended by using the evidential reasoning method and Fuzzy set theory in combination with the proposed models.

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