PREDICTIVE RISK MODELLING WITH BAYESIAN NETWORK FOR MARITIME APPLICATIONS

ZHANG GUIZHEN

Interdisciplinary Graduate School

Nanyang Environment and Water Research Institute

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SUMMARY

Maritime accidents have so far still occurred frequently, threatening the safety for seafarers at sea, the economic performance of shipping companies and the sustainability of the environment. One way to improve maritime safety and reduce the related pollution is to carry out the Formal Safety Assessment, a rational and systematic process to assess the risks associated with shipping activities and evaluate the cost effectiveness of potential risk control options (RCOs). The increasingly popular Bayesian Network (BN) method has been recommended for risk assessment (Step 3 of FSA) to the International Maritime Organization (IMO). However, issues of “data availability”, “data quality” and “dependence on experts” all challenge the use of BN for maritime applications. Therefore, this study aims to enhance the BN methodology to address the limitations of the data constraint for maritime accidents prediction. The modelling of both the Low Probability, High Consequence (LP-HC) accidents and High Probability, Low Consequence (HP-LC) accidents are addressed in this study, with consideration of their inherent differences in nature.

The extension of traditional BN with interval probabilities was proposed in the present study for the modelling of LP-HC accidents, for which probability elicitation from experts is the main source both for model structure construction and parameterization. The elicited probabilities often carry different levels of uncertainty due to incompleteness in human knowledge, since experts are not only asked about their own expertise but also about the probability of others’ failures during the elicitation process. Interval probability numbers can represent the imprecision in the experts’ judgement. The extended BN with interval probabilities was applied to the predictive modelling for ship collision causation probability, which enabled the quantification of epistemic uncertainty explicitly in the risk assessment results. An excel-based elicitation tool was developed, utilizing linguistic terms, which allowed rapid elicitation of conditional interval probabilities. Inferences

were made directly with the interval probability parameters. Different levels of discrepancies were revealed from the computed results using inputs from different experts, which in turn verified the existence of uncertainty in risk modelling. A discussion was also provided on how the uncertainty in risk assessment propagated to the decision-making process and influenced the ranking of potential RCOs.

Probabilistic modelling of the seafarers' occupational accidents and injuries was then studied as a stereotype of the HP-LC accidents. Compared with the LP-HC accidents, modelling of the HP-LC accidents does not need to rely on the experts' opinions, since more data could be obtained due to their higher occurrence frequency. Therefore, an extensive empirical survey was carried out using a carefully designed questionnaire, to collect first hand data about the seafarers' injury experience as well as their behavioral safety practices regarding the potential risk factors. Unlike the historical injury accident databases, the survey captured information for both the accident and ordinary cases, which enabled the probabilistic prediction for the injury occurrences. Meanwhile, the survey data supplemented the experts' opinion by allowing the verification of potential risk factors with empirical data. The predictive BN model was built consisting of the major risk factors identified from the survey. Insightful results regarding the frequency, circumstances, and causes of injuries aboard merchant ships were discovered. Finally, the BN model was verified with several validation tests.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

AHP	Analytic Hierarchy Process
EMSA	European Maritime Safety Agency
IPE	Iterated Partial Evaluation
2U	An updating algorithm for binary polytree structured credal networks
ABS	American Bureau of Shipping
AIS	Automatic Identification System
ANN	Artificial Neural Network
ARPA	Automatic Radar Plotting Aid
ATSB	Australian Transport Safety Bureau
ATSB	Australian Transport Safety Bureau (ATSB)
BBN	Bayesian Network
BE	Basic Events
BIMCO	Baltic and International Maritime Council
BRM	Bridge Resource Management
CART	Classification and Regression Trees
CHAID	Chi-Squared Automatic Interaction Detection
CN	Credal Network
COLREG	International Regulations for Preventing Collisions at Sea
CPT	Conditional Probability Table
CT	Classification trees
DAG	Directed Acyclic Graph
DNV	Det Norske Veritas
D-S	Dempster-Shafer
DTS	Decision-theoretic specification
ECDIS	Electronic Chart Display and Information System

ELM	Extreme Learning Machines
EMCIP	European Marine Casualty Information Platform
ENSI	Enhanced Navigation Support Information
ETA	Event Tree Analysis
EU	European Union
FAHP	Fuzzy Analytical Hierarchy Process
FMEA	Failure Mode Effects Analysis
FOC	Flag of Convenience
FSA	Formal Safety Assessment
FTA	Fault Tree Analysis
GCAF	Gross Cost of Averting a Fatality
GISIS	The Global Integrated Shipping Information System
GL2U	An Updating Algorithm for Any Credal Networks
GPS	Global Positioning System
GRACAT	Grounding and Collision Analysis Toolbox
HAZOP	Hazard and Operability Analysis
HFACS	Human Factors Analysis and Classification System
HP-LC	High Probability, Low Consequence
HSE	Health and Safety Executive
IF	Internal Factors
IMO	International Maritime Organization
IPT	Interval Probability Theory
ISESO	Increased Safety and Efficiency in Ship Design and Operation
L2U	An updating algorithm for binary credal networks
LHS	Left Hand Side
LP-HC	Low Probability, High Consequence
LR	Logistic Regression

MAIB	Marine Accident Investigation Branch
MOFs	Management and Organizational Factors
MoU	Memoranda of Understanding
NBR	Negative Binomial Regression
NCAF	Net Cost of Averting a Fatality
NP	Non-deterministic Polynomial
NPV	Net Present Values
OOBN	Object-Oriented BN
OOW	Officer on Watch
PEC	Pilotage Exemption Certificate
PSFs	Performance and Shape Factors
QUEST	Quick, Unbiased, Efficient Statistical Tree
RCC	Rescue Coordination Centre
RCO	Risk Control Options
RHS	Right Hand Side
SHEL	Software, Hardware, Environment, Live ware
SLP	Support Logic Programming
SRS	Sub Research Questions
STRAITREP	The Mandatory Ship Reporting System in the Straits of Malacca and Singapore
SV2U	Structured Variational Methods
SVM	Support Vector Machines
TSB	Transportation Safety Board of Canada
TSS	Traffic Separation Scheme
UNCTAD	United Nations Conference on Trade and Development
VTS	Vessel Traffic Service

CHAPTER 1 Introduction

1.1 Research Background

1.1.1 Trends of the seaborne trade and maritime accidents

1.1.1.1 Growth of the shipping industry and seaborne trade

Competitive costs, huge carrying capacities and reduced turnaround times have made shipping the most common and efficient mode of transportation. At present, 90% of the world trade is carried by shipping (Kaluza, Kölzsch, Gastner, & Blasius, 2010). As of 2016, the world's fleet consists of 90,917 registered vessels, with a total tonnage of 1.81 billion dwt (UNCTAD, 2016) and employing approximately 1.65 million seafarers all over the world (BIMCO; ICS, 2015). Despite the downturn of the world's economies after the financial crisis in 2008, the long-term outlook remains promising. A continuous growth of the world's seaborne trade was predicted by the International Chamber of Shipping (ICS) in 2016, in line with the expected increase in economies and population, as shown in Figure 1-1, which drives the future prosperity of the shipping industry.

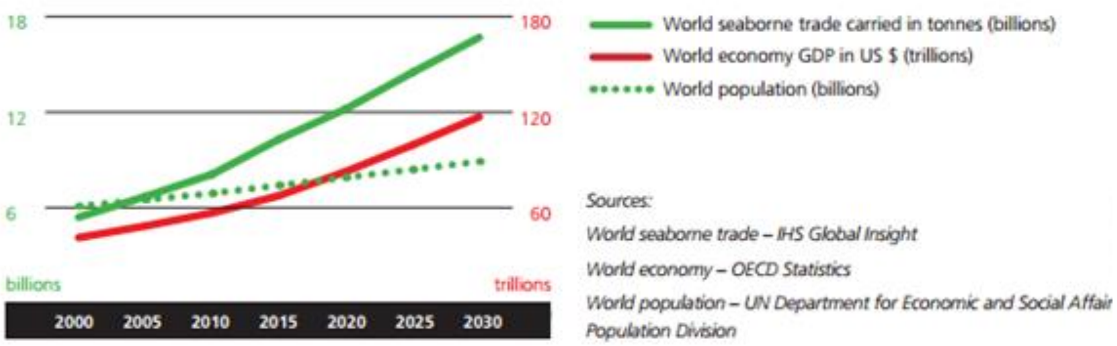


Figure 1-1 Prediction of the world seaborne trade, GDP and population

Source:(International Chamber of Shipping, 2016)

1.1.1.2 Types of shipping accidents and their consequences

Even though shipping has been regarded as the safest mode of transportation, shipping accidents have persisted, threatening the lives of people at sea, the economic performance of shipping companies and the wellbeing of the environment.

Figure 1-2 shows the three major categories of shipping accidents, including work accidents, vessel accidents and maloperations. The detailed accident types within each category as well as their potential consequences are also illustrated in this figure. Most of the vessel accidents, such as ship collisions and groundings, are rare occurrences but can yield catastrophic consequences including environmental damages, and thus can be categorized as Low Probability-High Consequence (LP-HC) accidents (Elliott, Kleindorfer, DuBois, & Wang, 2008). On the other hand, the work accidents aboard ships occur more frequently with less severe damage potentials, and can be categorized as High Probability- Low Consequence (HP-LC) accidents.

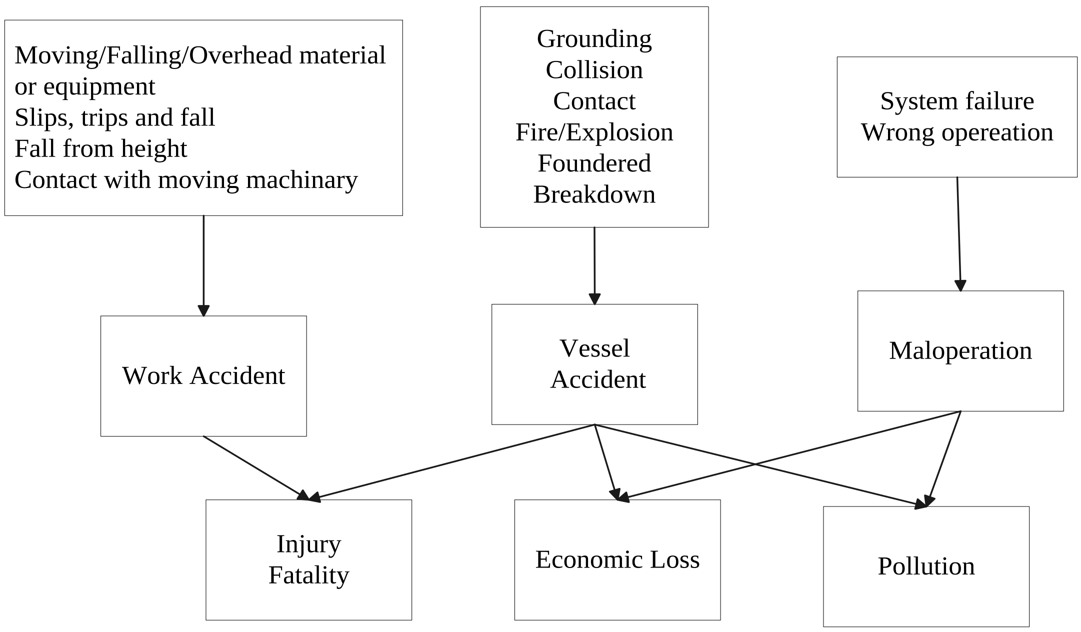


Figure 1-2 Maritime accident types and consequences

Source (Kristiansen, 2013)

The safety performance of shipping companies is often measured in two dimensions: (a) the personal health and safety performance dimension and (b) the operational safety dimension, as shown in Table 1-1 (ABS, 2012). The former is more focused on people, while the latter is more concerned with vessel operations.

Table 1-1 Safety performance measurement (ABS, 2012)

Occupational Health and Safety measurement	Operational Safety measurement
Total Recordable Cases Frequency (TRCF)	Operational Incidents Frequencies
Lost Time Incidents Frequency (LTIF)	Near Miss Frequencies (NMF)
Medical Treatment Case Frequency (MTCF)	Conditions of Class Frequencies
Restricted Work Accident Frequency (RWAF)	Port State Deficiencies Frequencies

1.1.1.3 Trends of maritime accidents

Even though the number of total loss of ships is declining, as seen in Figure 1-3, the number of maritime casualties is almost constant according to the Lloyd's List Intelligence Casualty Statistics or even gradually increasing based on data from European Marine Casualty Information Platform (EMCIP), as shown in Figure 1-4.

Maritime casualty refers to any event that caused damage to a person, a ship, its cargo or equipment on board, regardless of the seriousness of the event. According to the data from EMCIP, the number of casualties associated with vessels rose from 898 to 2047 from the year 2011 to 2014, while the number of occupational accidents increased continuously from 373 to 978. These numbers may not be accurate considering the phenomenon of under reporting, but the trend indicates that the occurrences of casualties are still posing challenges to the maritime industry.

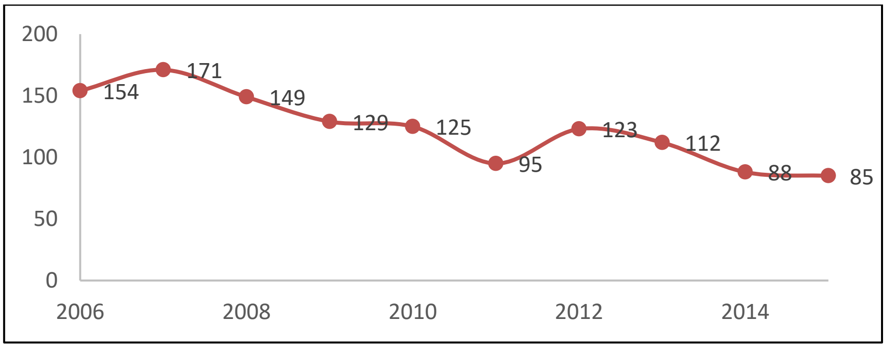


Figure 1-3 Number of total loss of ships from 2006 to 2015

Source (Whitehead, 2016)

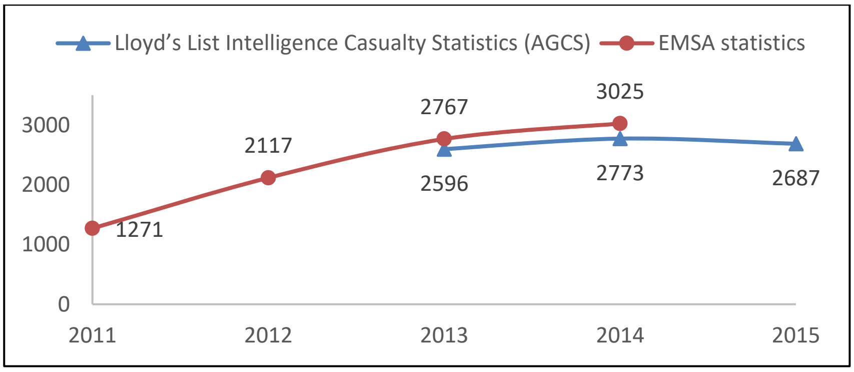


Figure 1-4 Number of maritime casualties from 2011 to 2015

Source (Whitehead, 2016) (EMSA, 2015)

1.1.2 Maritime safety regulations

1.1.2.1 Maritime stakeholders and their roles in safety management

One of the primary concerns in the maritime domain is to improve safety and reduce pollution caused by shipping accidents and incidents. The responsibilities for ensuring shipping safety are to be borne by all stakeholders in the maritime domain, including International Maritime organization (IMO), port state control authorities, classification societies, cargo owners and most importantly shipping and ship management companies. Figure 1-5 displays the main stakeholders and their inter-relationship for maritime safety.

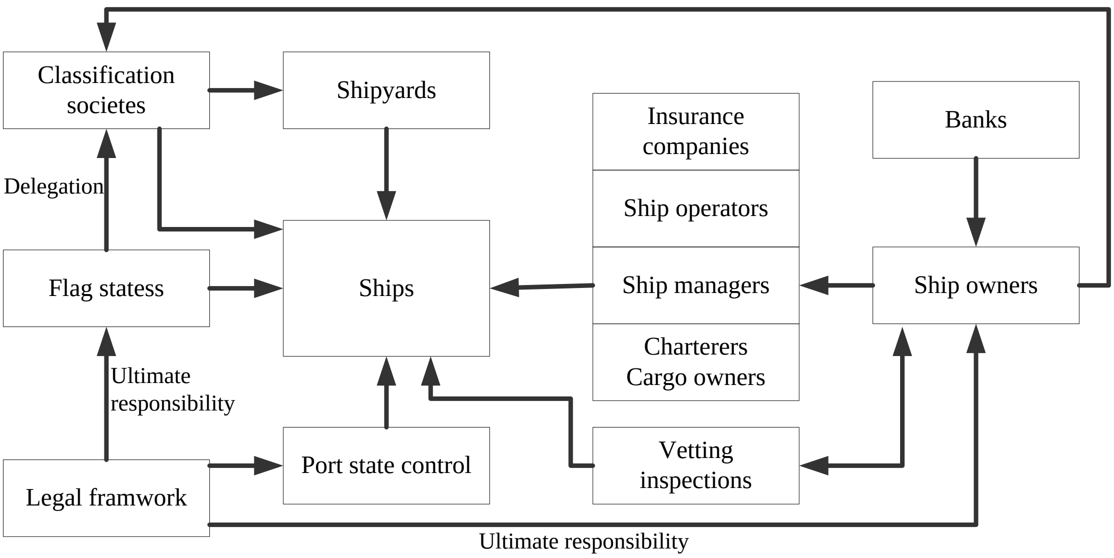


Figure 1-5 Stakeholders and their inter-relationship for maritime safety

Source (Jalonen & Salmi, 2009)

IMO, flag states and port states are the primary regulating organizations. IMO governs the maritime industry with a comprehensive legal framework. It continuously promotes safety by adopting new conventions and making amendments to the existing ones. The adopted conventions usually go through a long process of ratification and are finally to be enforced by the flag states. As of Dec 2016, 66 conventions or protocols have been adopted by IMO, among which 53 are already in force (International Maritime Organization, 2016).

However, due to the failure of flag states, especially for the advent of Flag of Convenience (FOC), port states are playing a more and more important role for the enforcement of safety rules, by verifying the competence of crews and inspecting ships on their visits of national ports. Substandard ships are required to rectify within a given period or be detained, depending on the level of noncompliance. Since the foundation of Paris Memoranda of Understanding (MoU), nine regional MoUs have been signed for information sharing and collaborations. The existence of port state control and MoUs has contributed to reduce the number of substandard ships, even though the principal enforcement responsibility still lies with the flag states.

The classification societies ensure shipping safety by setting and maintaining technical safety standards. It is also a common practice for the flag states to delegate the inspections to classification societies through their international surveyor network.

The primary compliance responsibility lies with the ship owners, operators and managers. Their management decisions regarding areas such as ship navigation, cargo handling and maintenance can have direct impacts on the safety of the ship at sea (Koester, 2001). Meanwhile, they bear the consequences or losses whenever accidents take place. Therefore, many shipping companies are keen on improving the safety standard of their ships. Other stakeholders, such as shipyards, banks and insurance companies, are also actively involved or affected by safety related issues.

1.1.2.2 International rules and conventions governing maritime safety

Shipping is regarded as an international industry not only because of the scope of cargo movements and the diversity in the compositions of seafarers, but also because of the international nature of the regulations governing the industry. These regulations cover various aspects and form a comprehensive legal framework, out of which maritime safety accounts for a big part. Table 1-2 shows some principal international conventions by IMO and International Labour Organization (ILO), which are aimed at improving maritime safety and reducing pollution by regulating the ships, the shipping companies and the seafarers. The requirements of these conventions prescribe the minimum standard for compliance, but the shipping companies are encouraged to do more to achieve higher standards in safety.

Table 1-2 Principal international regulations regarding maritime safety ICS (2016)

No.	Name of the convention/regulation	Regulated body
1	International Convention for the Safety of Life at Sea, 1974 (SOLAS)	The ship
2	International Convention for the Prevention of Pollution from Ships, 1973/1978 (MARPOL)	The ship
3	Convention on the International Regulations for Preventing Collisions at Sea, 1972 (COLREG)	The ship
4	International Convention on Load lines, 1966 (LOADLINE)	The ship
5	The International Ship and Port Facility Security Code, 2002 (ISPS)	The ship
6	The International Safety Management Code, 1993 (ISM)	The shipping company
7	International Convention on Standards of Training, Certification and Watch keeping for Seafarers, 1978/1995/2010 (STCW)	The seafarers
8	The ILO Merchant Shipping (Minimum Standards) Convention, 1976 (ILO 147)	The seafarers

1.1.2.3 Accidents reporting and investigation practice

Figure 1-6 shows a classical reporting line of accidents. The crew and ship masters on board are at the front line, who witness the accident in the first place. They normally report to their company, who will in turn forward to the flag state. Alternatively, the accident may be detected by the Vessel Traffic Service (VTS) or Rescue Coordination Centre (RCC). Near misses refer to cases where serious accidents could have happened. Reporting of near misses is also strongly encouraged. The reporting system of many companies and organizations typically covers both accidents and near misses.

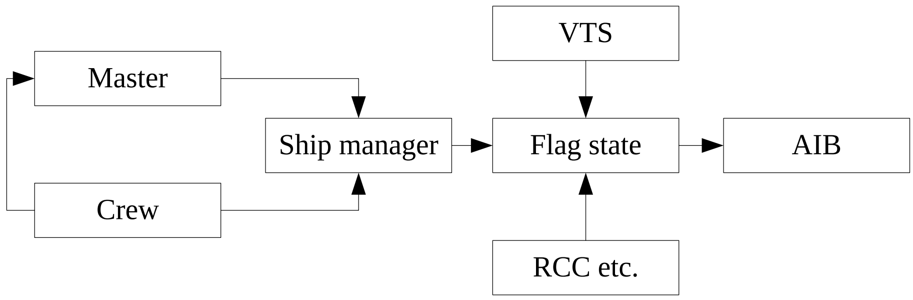


Figure 1-6 Accidents reporting path

Source (Hole, 2010)

According to the IMO casualty investigation code, it is mandatory for the flag state to investigate the accidents that happen to the vessels either registered under its flag or sailing in its water territories, as long as such investigations could lead to improvement in safety or when serious damage occurs. There exist many national accident investigation boards to conduct the investigations, such as the Marine Accident Investigation Branch of UK (MAIB), Transportation Safety Board of Canada (TSB) and Australian Transport Safety Bureau (ATSB). The investigation reports from these organizations can be easily accessed by the public, with detailed documentation of the occurrence and the lessons learnt.

Some regional platforms have also been established for information sharing purpose. For example, EMCIP gathers information about accidents from its member states in European Union (EU) (Ladan & Hänninen, 2012). The Global Integrated Shipping Information

System (GISIS) operated by IMO, maintains the casualty information worldwide. The Equasis platform integrates information from many sources, where any individual person or company can become a data provider of safety and quality information related to shipping. The current data providers include IHS, the port states regimes, classification societies, insurance companies, international maritime organizations and private shipping companies.

Accident reporting and investigations could help increase the safety awareness. However, the accident and near miss data contained in different databases may be overlapping. Meanwhile, the phenomenon of under reporting pervades. Many barriers prevent truthful reporting from the crew and the shipping companies. The crew might be afraid of being punished by the company while the shipping company might withhold such information to maintain its reputation. Even when non-blame safety culture is promoted in the company, the crew (especially junior crew like ratings) may still face difficulties in deciding what to report, or may be too busy, lazy or unconfident to write the report (Tapaninen, 2012). These obstacles must be tackled in the future to reduce under reporting.

1.1.3 Risk concept and Formal Safety Assessment

Since it is impossible to eliminate maritime accidents, the reasonable target is to mitigate accidents by decreasing the probability of their occurrence and minimizing the severity of the associated consequences, i.e. minimizing the risk of accidents. Risk assessment is a structured science-based process to estimate the likelihood and severity of accidents with attendant uncertainty (Coleman & Marks, 1999). It is defined through events A, probability P and consequence C, i.e. Risk ~ (A, P, C), and mainly deals with questions like ‘what could go wrong’, ‘what is the probability of the occurrence’ and ‘what could be the potential consequences’.

Risk assessment has been a hot topic in the last two decades in the maritime and offshore industry. IMO has proposed the systematic Formal Safety Assessment (FSA) (Kontovas & Psaraftis, 2009) for risk assessment and cost effectiveness evaluation to aid decision making in safety management. The five components for FSA analysis are: 1. Hazard identification, 2. Risk Assessment, 3. Risk control options (RCOs), 4. Cost-benefit Analysis, and 5. Recommendations for decision making (Figure 1-7).

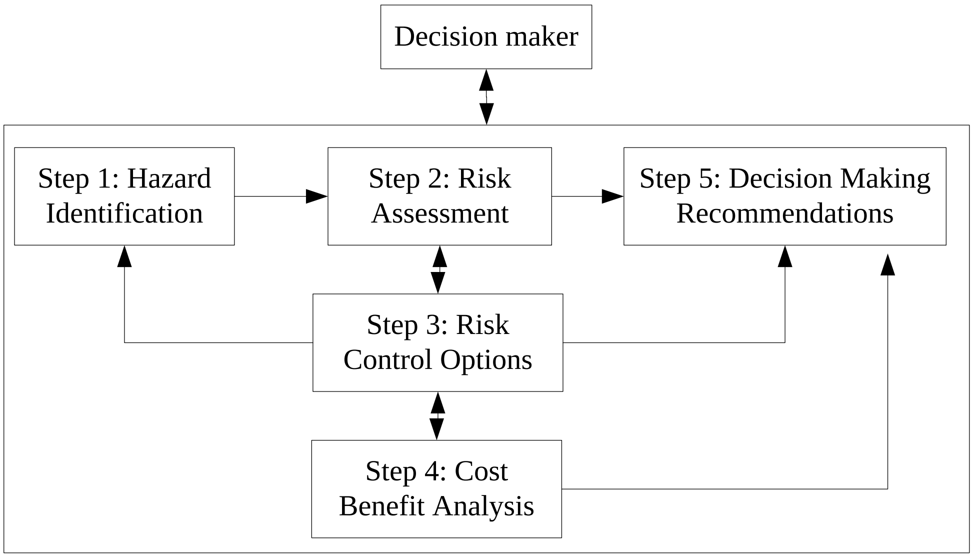


Figure 1-7 Framework for the Formal Safety Assessment

Source (Embankment, 2002)

Risk assessment, can be simple qualitative risk profiling or visualization through establishing the risk matrix. It can also be complicated quantitative analysis with detailed models for probability and consequences estimation. Risk assessment, especially quantitative risk assessment, enables the evaluation of the current risk level as well as the identification of areas for improvements, which forms the basis for deriving potential control options as well as their cost-benefit analysis.

1.2 Research scope, motivation and methods

1.2.1 Research scope

This study focuses on developing predictive risk models for maritime accidents, which can lead to both personal and environmental damages. More attention is paid to the probability prediction, since the most cost-effective way to manage risks of many maritime accidents is to reduce their probabilities of occurrence (P Terndrup Pedersen, 2010). Accident consequence modelling is beyond the scope of this study. Probabilistic modelling of the two typical accident types described in Section 1.1.1.2, i.e. both LP-HC accident and the HP-LC accidents, will be studied.

Meanwhile, uncertainty, including aleatory uncertainty (probabilistic) and epistemic uncertainty (cognitive) (Merrick, Van Dorp, & Dinesh, 2005), is inherent to risk analysis, the proper treatment of which is of high relevance (O.-V. E. Sormunen et al., 2014). The former is associated with the randomness of a system, while the latter can be attributed to the lack of knowledge about the system and in turn about model's parameters (J. Liu, Yang, Wang, & Sii, 2003) (Merrick et al., 2005) (Fallet, Duval, Simon, Weber, & Iung, 2011). However, the existence of uncertainty in risk analysis has been well recognized, yet seldom addressed for risk assessment. This research will exploit innovative ways to deal with uncertainties in risk assessment of maritime accidents, to allow risk informed decision making.

1.2.2 Bayesian network as a methodology for maritime risk analysis

Many risk analysis methods have been developed and applied during the past few years, including Hazard and Operability Studies (HAZOP), Failure Mode and Effects Analysis (FMEA), Event Tree Analysis (ETA), Fault Tree Analysis (FTA) and Bayesian Network (BN). BN stands out compared to the conventional risk analysis methods such as FTA for several reasons.

First, BN has the capability to model causal interdependencies and common causes (Trucco, Cagno, Ruggeri, & Grande, 2008). This additional capacity make it suitable for modelling maritime accidents since many basic events are influenced by the same factors at organizational levels. Second, it can incorporate experts' knowledge when statistical data do not exist, which enables the quantification of influences of the human and organizational factors, which are the underlying causes for most maritime accidents yet not possible to be quantitatively captured by the conventional methods. Third, it has abductive reasoning capabilities as well as conductive capability, and thus can generate diagnostics with observations of accident occurrences in addition to the predictive analysis power to calculate the scenario occurrence probability (Khakzad, Khan, & Amyotte, 2011). Meanwhile, BN is a very flexible method which dynamically makes updates with new observation or evidences about some nodes in the model.

1.2.3 Rapid Growth of BN applications for maritime safety analysis

BN has been a popular methodology for dependability, risk and maintenance analyses (Weber, Medina-Oliva, Simon, & Iung, 2012) due to these good features. The application of BN for risk analysis dated back to 1996 and grew rapidly after 2001. The number of articles increased 4 times since then to 2008. BN also became increasingly popular for the maritime risk modelling during the last decade. The number of publications in Scopus containing the keywords of "maritime safety" and "BN" increased from 0 to 16 during the period of 2004-2013, as seen in Figure 1-8 (Hänninen, 2014). BN was also proposed for risk assessment (Step 3 of the Formal Safety Assessment, FSA) to IMO (Hänninen & Kujala, 2009).

A detailed review of the application of BN as a tool for the risk assessment of the maritime transportation system can be found in Chapter 2 and Chapter 3, with a focus on the data sources and techniques for the probability elicitation.

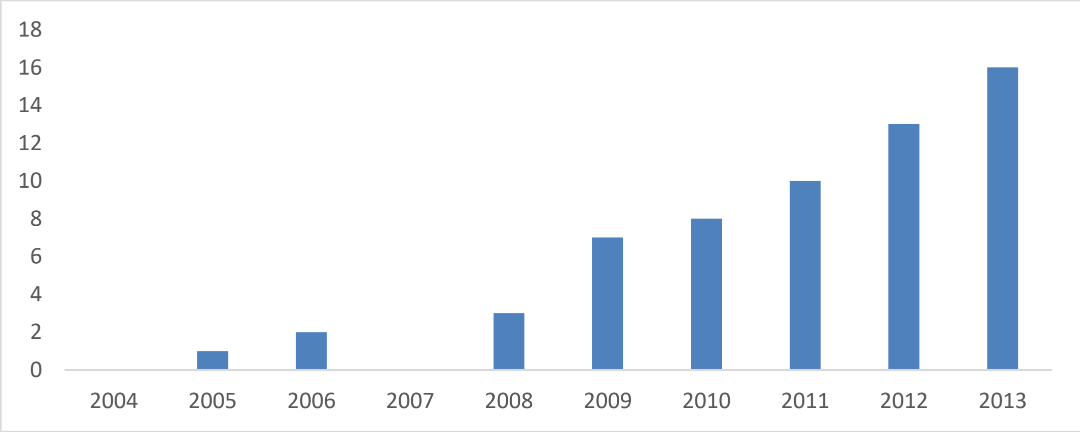


Figure 1-8 Number of BN applications for maritime safety published in Scopus

Source (Hänninen, 2014)

1.2.4 Challenges for BN applications due to data availability

The application of BN includes three steps, i.e. constructing the BN structure, obtaining the relative parameters, and making inferences. Both the BN structure and parameters can be obtained manually, automatically or from a combination of both (Kjrćulff & Madsen, 2013; Neil, Fenton, & Nielson, 2000). A major problem often criticized of BN is its demands for a large number of precise conditional probabilities, which poses a great challenge in applications. Data driven BN modelling is always difficult due to data availability. Problems of accessibility, usability and compatibility exist, not to mention the huge number of probabilities to define. For example, even when accident database and accident reports are available, they cannot be used for the probability prediction of the related accidents because they do not contain information on ordinary cases.

Therefore, in most cases, knowledge elicitation from the domain experts is an important source for the probability specification (Knochenhauer et al., 2013). An expert is a person who is recognized (by peers, decision makers, or others) for their skills, knowledge, and expertise in a particular domain of interest (Szwed & Van Dorp, 2002). However, even though it is an advantage of BN to utilize the experts' opinions to facilitate the modelling of events with scarce data, the probability elicitation process poses great challenges for experts. First, it is difficult for the experts to provide the exact probabilities with confidence when there is little or incomplete data available, especially considering that the experts are asked about the probability of others' failures on top of their own expertise in the elicitation process. Moreover, the tremendous workload for providing the great number of conditional probabilities makes it worse. As a result, the exact probabilities obtained from experts' judgments often carry high levels of uncertainty.

Therefore, this research explores different approaches to reduce and represent the uncertainties with BN taking into account the nature of the accidents to model.

1.3 Research objectives and framework

1.3.1 Research objectives

The focus of the main research questions is: how to build predictive risk models with BN for different types of maritime accidents? Under this main research question, several Sub Research Questions (SRQ) are addressed, as listed below.

SRQ 1: What are the contributing factors/predictors and how to include the different types of causal factors into the same model?

Shipping is a large-scale system involving many components. The causal factors cover a wide range, including technical factors, environmental factors, as well as human and organizational factors. How to identify the most relevant contributing factors as predictors and to include different clusters of causal factors in the same model is the first SRQ.

SRQ 2: Where can data be obtained and how can they fit in, to build quantitative risk models for the LP-HC accidents and HP-LC accidents respectively?

Maritime accident modelling is an area constrained by scarce data. This is especially the case for the LP-HC accidents, where a large number of causal factors are involved but only very limited historical data are available. Problems, such as under-reporting and errors in reporting and missing data, also add to the difficulties. In addition, many data may not be accessible for research purpose, like the confidential safety databases maintained by individual shipping companies. Meanwhile, some data, for example the accidents reports in text format, can not be directly used for modelling without pre-coding. Moreover, data from different sources are always incompatible due to the differences in data structures. All these challenges drive the need for specific designs of methods to collect data for modelling.

SRQ 3: How to reduce or represent uncertainties in risk modelling with BN, especially when experts' knowledge is involved?

As mentioned before, uncertainty in risk modelling has been well recognized but rarely discussed. BN can address the aleatory uncertainty through the probability concept itself. However, the epistemic uncertainty due to incomplete knowledge about model parameters, i.e. conditional probabilities, remains a big challenge, especially when the experts' judgements are employed. Therefore, this study explores the extension of BN with interval probabilities for the maritime risk modelling to represent epistemic uncertainties.

SRQ 4: How will the decision-making process be affected by the uncertainties in the risk assessment results?

Risk assessment provides the basis for decision making for risk management and prevention. The traditional BN method requires the user to provide exact probability numbers and produces exact probabilities as output as well, which is quite straightforward for use in decision making. However, when imprecise probabilities are obtained during the risk analysis process, the complexity increases. It is of interest in this study to examine how the decision-making process can be affected when uncertainties are considered.

The main objective of this study is to improve the risk modelling process for the maritime accidents to enhance the risk related decision making.

1.3.2 Research framework overview

Figure 1-9 illustrates the research framework of this thesis.

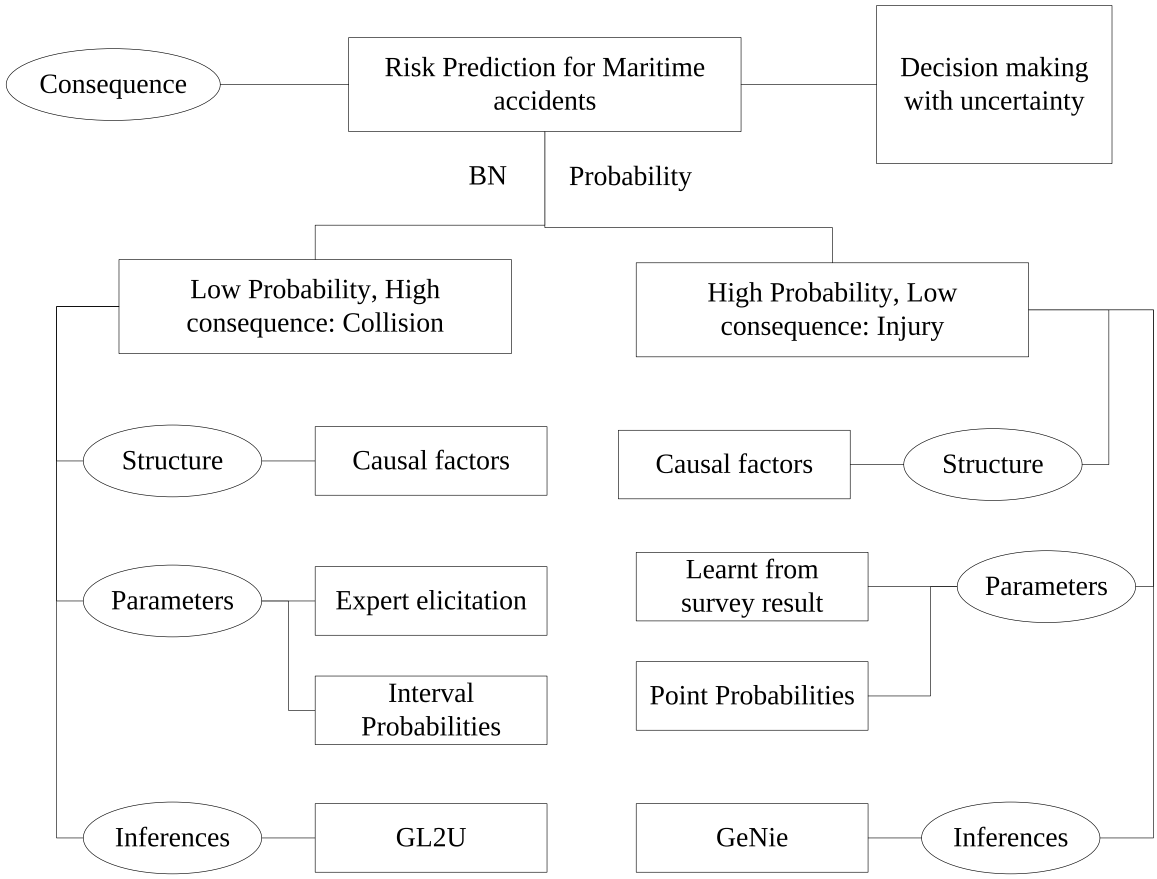


Figure 1-9 Research framework for the thesis

Source (Author)

Ship collision was selected for study as a stereotype of the LP-HC accidents while the more frequent seafarer injuries were chosen as the HP-LC accidents. Even though the same method BN, was used as the methodology, the data sources of the two cases are totally different.

To be more specific, the parameterization of the collision model would be built based on experts' opinions. To represent the epistemic uncertainty related to the experts' judgement, interval probabilities (with an upper bound and lower bound) rather than point values would be used as parameters. An elicitation tool with a probability scale was built to facilitate the elicitation process. Inference was to be made with the GL2U algorithm for the interval BN. On the other hand, to reduce the epistemic uncertainty, modelling for the seafarer injuries was based on an empirical survey. The parameters for the injury model were learnt from the survey data.

1.4 Organization of the thesis

The rest of the thesis is organized as follows.

Chapter 2 is the literature review section. Separate literature reviews are conducted on ship collisions and seafarers' occupational injuries, as the representative events of LP-HC accidents and LP-HC accidents respectively. The literature on ship collision risk assessment has been arranged in two categories, i.e. the two-step methods and the one-step methods. The former is discussed in more detail for its popularity, including a general description of the framework, a summary of existing geometrical probability models and a summary of causation probability models. Meanwhile, three main streams of literature are reviewed for the occupational accidents and injuries, for both the maritime sector and other sectors. The first stream comprises the qualitative studies and simple quantitative studies using descriptive statistics. The second stream focuses on the data mining of historical accident records, and the third stream discusses the quantitative risk models with inputs from experts' opinion. Finally, gaps of the literature regarding both accident types are identified based on the literature review.

Chapter 3 presents the methodologies. First, the basics of BN theory, the concepts of conditional probabilities as well as the BN updating algorithms are introduced, to provide an overview of the BN method. Next, the benefits and major challenges of BN in applications are discussed, particularly for the maritime accidents modelling. Techniques for reducing the elicitation burden as well as the methods for elicitation of individual probabilities are reviewed and summarized. A discussion is also provided on the applications of the reviewed techniques in the maritime BN models. Next, the extension of BN with interval probabilities (a special type of Credal Network, CN) is introduced to address the epistemic uncertainty, especially when the experts' opinions are employed for model parameterizations. The definition of CN, the properties of interval probabilities and the relative updating algorithms are presented subsequently. The last part of Chapter 3 describes the data collection process for the modelling of both accident types. The development of the elicitation tool as well as the probability combination process are described for the collision modelling. Meanwhile, the questionnaire design and administration for the empirical survey on seafarers' occupational injuries are also stated.

Chapter 4 discusses in detail the construction and computation of the collision causation probability model, utilizing the extended BN with interval probabilities. First, the causal factors for ship collisions are identified, based on which the state of the art causation model is established. A brief view of the elicited conditional probabilities, an illustration of the probability combination process as well as the assumptions for the prior probability distributions are presented afterwards, while the complete combined Conditional Probability Table (CPTs) for all nodes are attached in the appendix at the end of this thesis. Inferences using the extended BN with the elicited interval probability parameters are presented next. Comparisons of results from GL2U algorithm and the traditional BN software GeNie are provided. Meanwhile, cross comparisons of results from different experts are also discussed. Finally, the influence of the uncertainty in risk assessment results on the decision-making process is illustrated through a simple example.

Chapter 5 presents the detailed study for the probabilistic modelling of seafarer's injuries. The potential risk factors identified from the literature are presented first, based on which the survey questionnaire is designed. Next, an overview of the respondents' profile is provided before a data summary in the form of two-way contingency table. Discoveries on the injury patterns are briefly discussed based on the aggregated data. Due to the existence of very small numbers for some risk factors, a binarization step is added. Preliminary results with chi-square tests are presented which verify the significance of the binarized risk factors. Next, the findings from the association rules analysis are listed, which provides the knowledge on the structure establishment of the predictive BN model. Inferences using the BN model for predictions regarding the injury probabilities are discussed subsequently. Finally, the results of several validations tests are presented.

Chapter 6 concludes the thesis. First, the contributions of the research are summarized, followed by some general recommendations on the practical applications of the current models. Things to take note for future risk assessment model development and applications are also pointed out. The last subsection provides a discussion on the limitations of the current study and proposes several potential future research directions.

CHAPTER 2 Literature review

2.1 Review of the risk assessment models for ship collision accidents

Statistics have shown that navigational accidents such as collision, contact and grounding are the most common types of shipping accidents. For example, from a survey of total loss accidents recorded over 25 years, it was found that stranding resulted in the most fatalities on board merchant vessels (Kuehmayer, 2008). Similarly, groundings accounted for 47.6% of all accidents that occurred in the Gulf of Finland from 1997 to 2006 based on the DAMA database, followed by the 20.0% for ship-ship collisions (Kujala, Hänninen, Arola, & Ylitalo, 2009). In the literature, numerous studies have been conducted on the risk assessment of ship collisions and groundings. Generally, these two types of accidents are quite similar in nature and are treated very similarly, either with a two-step method or being modelled as

a whole. The following subsection reviews the models for ship collisions.

2.1.1 Quantitative risk assessment framework for ship collisions: the two-step method

2.1.1.1 Overview of the two-step method

The two-step method is the most widely used method for collision risk analysis, i.e. the collision probability P is modelled as the product of the geometrical probability P_a and causation probability P_c (S. Li, Meng, & Qu, 2012).

$$P = P_a \times P_c \tag{2-1}$$

Geometrical probability refers to the probability of a ship becoming a collision candidate, which means that a collision would happen if no further evasive actions were taken. Causation probability is the probability that a collision candidate fails to conduct any evasive action and thus goes collided.

The following function is commonly used to calculate the number or frequency of collisions for a specific region over a period,

$$N = N_a \times P_c \tag{2-2}$$

where N is the number of collisions, N_a is the number of collision candidates for the considered area (also called encounters), and P_c is the causation probability. It should be noted that geometrical probability P_a could be regarded as the ratio between the number of collision candidates (N_a) and all passing ships.

Some papers differentiate the type of encounters depending on the encounter angle. Different causation probability numbers would be assigned for different types of encounters. The collision probability could then be obtained by summing up all types of encounters. Figure 2-1 shows the three major encounters defined in COLREG (Goerlandt & Kujala, 2011, 2014; O. Sormunen, 2011): a head-on encounter is defined if the struck ship is in the bow section within 5^{o} in either direction from the ship's centre line; an overtaking encounter is defined if the angle difference between the encountering ships does not exceed 67.5^{o}; and the remaining encountering situations are categorized into crossing encounters.

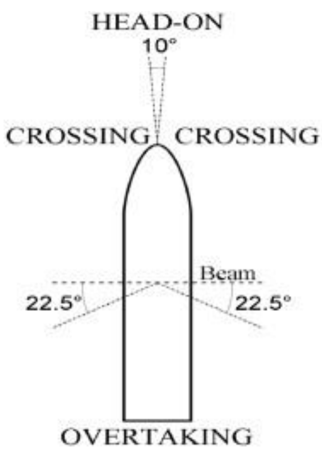


Figure 2-1 Encounter types defined by COLREG 1972

Source (Goerlandt & Kujala, 2011)

However, the criteria may vary. For example, Montewka, Hinz, Kujala, and Matusiak (2010); and Weng, Meng, and Qu (2012) adopted the 10^{o} ranges instead of the 5^{o} and 67.5^{o} mentioned above, meaning that head-on and overtaking encounters are defined when two ships are lying on almost reciprocal or parallel courses with less than 10^{o} angle difference respectively, while all other situations are classified as crossing encounters.

Many detailed models have been developed for both geometrical and causation collision probability estimation. Subsection 2.1.1.2 reviews the geometrical collision probability models and Subsection 2.1.1.2 reviews the causation collision probability models. In practical applications, the geometrical and causation probability are not always modelled in detail at the same time. In fact, only detailed geometrical probability models are needed for the calculation of the number or frequency of collisions for a specific geographic region, while simplified causation probability numbers from statistics or literatures can be used for such cases. On the contrary, detailed causation probability models are essential for accident management and prevention.

2.1.1.2 Geometrical probability models

Geometrical probability can be calculated with either analytical models or dynamic system simulations of the real traffic conditions. The existing geometrical probability estimation models are reviewed and summarized in Table 2-1. Some of the models provided explicit analytical functions for the calculation of geometrical probabilities, while some models provided ways to estimate the number of encounters. For simulation models, the criteria for encounter detection were compiled.

Table 2-1 Methods for calculating the geometrical probability or the number of collision candidates

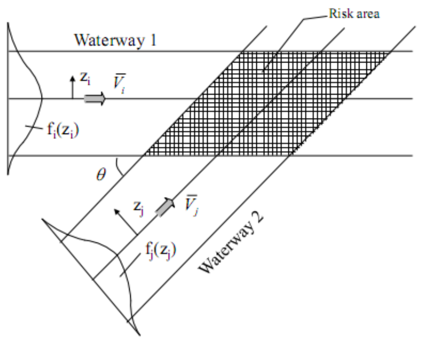
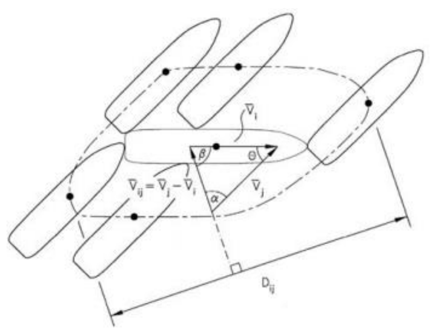
Sources	Description	Analytical function/ Encounter criterion	Comments
(Macduff, 1974) (S. Li et al., 2012)	(*Analytical*) Geometrical probability is linear to the travelling distance.	Geometrical probability: $P_a = \frac{X \cdot L}{D^2} \cdot \frac{\sin(\theta/2)}{925}$ D average distance between ships, X actual length of path to be considered by a single ship, L average ship length, θ crossing angle.	One main stream moving at constant V, another ship approaching the stream at V with angle θ. Over estimation exists when the angle θ is small. Speed assumption is not realistic and may result under estimation.
(S. Li et al., 2012)	(*Analytical*)	Number of encounters: $N_a = \int_{entrence}^{exit} \rho D_e V_{rel} / V dx$ ρ ship density, D_e diameter of evasion, V_{rel} relative speed, V speed of passing ship	Over estimation exists since D_e is conservative, being around 9.5 to 16.3 times of L.
(Preben Terndrup Pedersen & Zhang, 1999) (P Terndrup Pedersen, 2010) (Kujala et al., 2009) (S. Li et al., 2012)	(*Analytical*) Assumption is that traffic intensity, velocity, ship routes' lateral distributions are all known. Parallel waterway is a special case of crossing waterway where θ=0 or 180.	Number of encounters: $N_a = \sum_i \sum_j \int_{\Omega(Z_i Z_j)} \frac{Q_i^{(1)} Q_j^{(2)}}{V_i^{(1)} V_j^{(2)}} \cdot f_i^{(1)}(Z_i) f_j^{(2)}(Z_j) V_{ij} D_{ij} dA\Delta t$ Q_i, Q_j are the traffic movements on waterway 1 and waterway 2 during unit time, V_i, V_j are the velocity of ship 1 and ship 2, f_i, f_j is the lateral distribution of ship routes, z is the distance from centre line, V_{ij} the relative velocity, D_{ij} collision diameter.	Two-way waterway:  Collision diameter definition D_{ij} 

Table 2-1 Methods for calculating the geometrical probability or the number of collision candidates (continued)

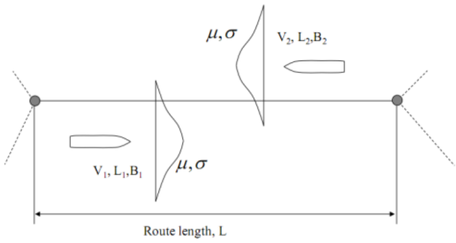
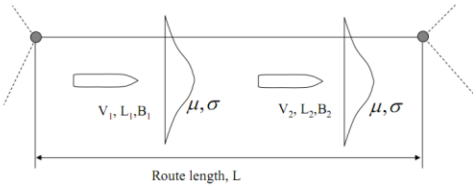
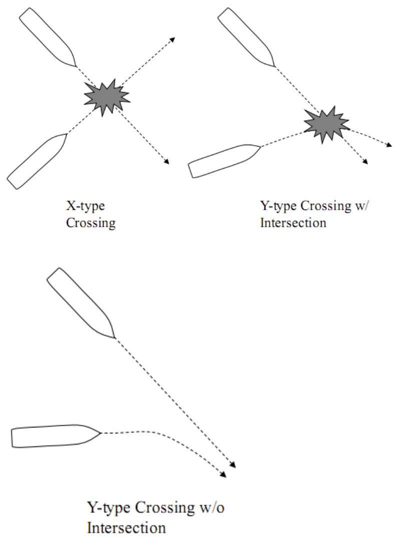
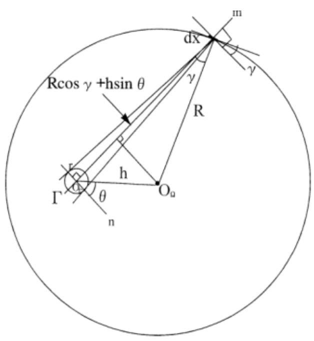
Sources	Description	Analytical function/ Encounter criterion	Comments
(S. Li et al., 2012) (COWI, 2008)	(*Analytical*)	(1) Parallel collision scenario: $P_a = P_T \times P_G$ $P_T = LN_1N_2\left\|\frac{V_1-V_2}{V_1V_2}\right\|$ $P_G = \frac{B_1 - B_2}{c}$ (2) Crossing collision scenario: $P_a = P_I \times P_G$ $P_I = \begin{cases} 1, & case1, case2 \\ 0, & case3 \\ 0.5, & case2or3 \end{cases}$ $P_G = N_1\left(1-e^{-N_2\Delta t}\right)$ *L length of route segment*, *N_1, N_2* are the yearly number of ship 1 and ship 2 passing, *V_1, V_2* are the velocity of ship 1 and ship 2, *B_1, B_2* are the width of ship 1 and ship 2, c *width of route segment*, θ crossing angle.	Parallel (Head-on)  Parallel (overtaking)  Crossing (case 1/ case 2/case 3) 
(Kaneko, 2002) (Montewka et al., 2010) (S. Li et al., 2012)	(*Analytical*) Encounter is counted when the distance between two ships are smaller than r.	Number of encounters by one ship in time T: (Random sailing) (1) Circular boundary $\lambda_c = \frac{4\rho VrT}{\pi}(1+a)E\left(\frac{2\sqrt{\alpha}}{1+\alpha}\right)$ $E\left(\frac{2\sqrt{V_0V}}{V_0+V}\right) = \int_0^{\frac{\pi}{2}}\sqrt{1-\frac{4V_0V}{V_0+V}\sin^2\theta}\,d\theta$	Circular boundary area: 

Table 2-1 Methods for calculating the geometrical probability or the number of collision candidates (continued)

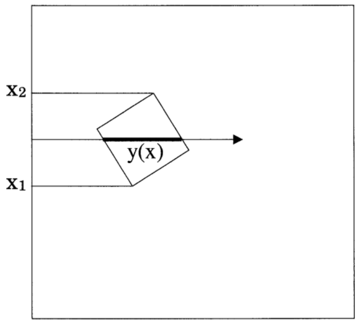
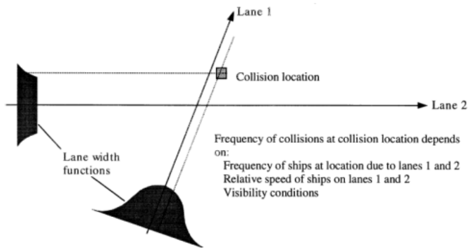
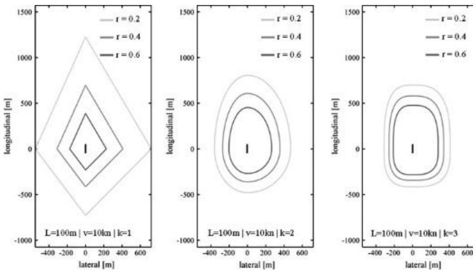
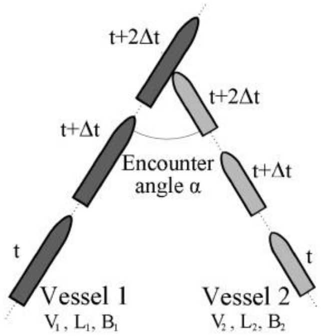
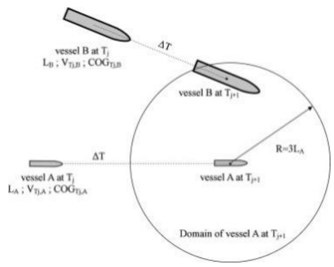
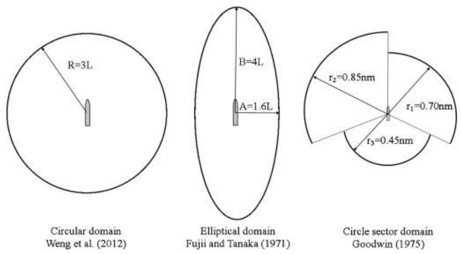
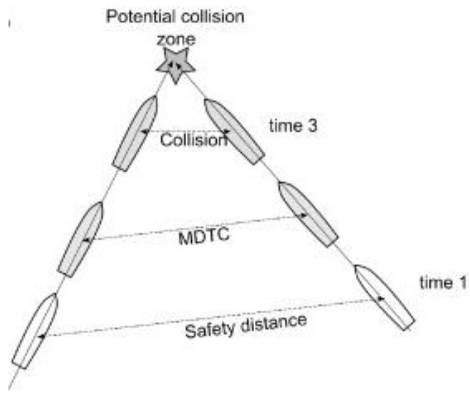
Sources	Description	Analytical function/ Encounter criterion	Comments
	Random sailing direction results 10% more encounters than fixed direction.	(2) Rectangular boundary $\lambda_c = \rho V 2rT\sqrt{1+\alpha^2+2\alpha\cos\theta}$ ρ average number of ship in the area, V_0 velocity of own ship, V velocity of other ship, $a = V_0/V$, r is chosen as 200m. θ direction between own ship and other ship	Rectangular boundary area: 
(Fowler & Sørgård, 2000)	(Simulation) Number of critical situation is derived from traffic image.	Collision conflict is detected when the distance between two ships are less than half nautical mile.	
(Qu, Meng, & Suyi, 2011) (Goerlandt & Kujala, 2014)	(Simulation) Traffic is simulated with AIS data.	Collision conflict is detected when two vessels' fuzzy quaternion ship domain (FQSD) overlaps.	Fuzzy quaternion ship domain (FQSD): 
(Goerlandt & Kujala, 2011) (Goerlandt & Kujala, 2014)	(Simulation) Blind navigation is assumed.	Collision is detected is detected when the contours of two ships overlap. Ship trajectories are predetermined and grouped based on AIS data.	

Table 2-1 Methods for calculating the geometrical probability or the number of collision candidates (continued)

Sources	Description	Analytical function/ Encounter criterion	Comments
(Weng et al., 2012) (Goerlandt & Kujala, 2014)	(Simulation) Traffic is simulated by directly applying the original AIS data.	Collision is detected when a vessel violates another vessels' domain. Example, Violation of circular domain: 	Ship domains: (circular, eclipse, circular sector) 
(Montewka et al., 2010)	(Simulation) MDTC changes for different encounter type and different ship type.	Collision could not be avoided by any manoeuvring when the distance between two vessels is smaller than MDTC. Ship manoeuvrability is taken into account.	

2.1.1.3 Causation probability models

Causation probability can be computed from historical accident statistics, adjustment of previous values, elicitation of experts' opinion, FT Analysis (FTA) and BN analysis (Mazaheri, 2009). FTA is a method that retraces the root causes of an accident using logic gate "AND" or "OR". Figure 2-1 shows an example of the FT model. In this example, the relationship between the accident and its direct causes (cause A, cause B and cause X) is modelled through an "AND" gate. Meanwhile, the relationship between the direct cause X and root cause C and D is modelled with an "OR" gate. The algebraic representation of the FT in Figure 2-1 is as follows:

$$P(\text{accident})=P(\text{cause A})\cap P(\text{cause X})\cap P(\text{cause B})$$

$$= P(\text{cause A})\cap P(\text{cause C}\cup \text{cause D})\cap P(\text{cause B}) \tag{2-3}$$

Normally, the original algebraic function can be reduced using the Boolean Algebra until the minimum cut sets are identified, which are simplified but equivalent representation of the original FT. The minimum cut sets for the example FT are ACB and ADB.

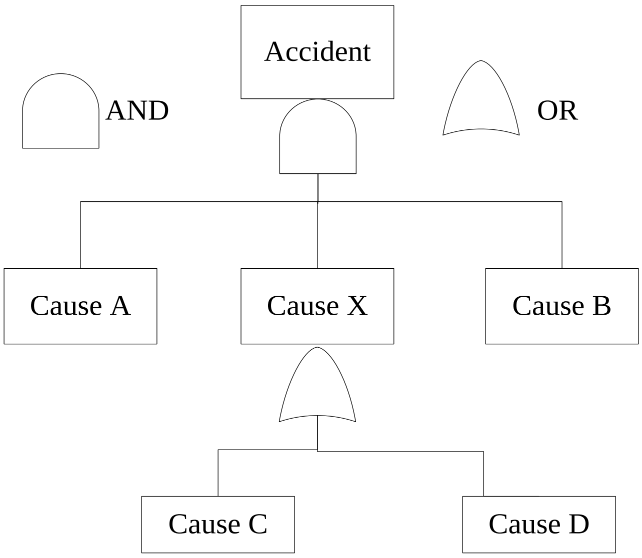


Figure 2-2 Example of a FT

Source (Uğurlu, Köse, Yildirim, & Yüksekyildiz, 2013)

The probability for the "AND" gate is:

$$P = \prod_{i=1}^{n} p_i \tag{2-4}$$

Similarly, the probability for "OR" gate is:

$$P = 1 - \prod_{i=1}^{n} (1 - p_i) \tag{2-3}$$

where p_i is the probability of a basic event.

In the literature, FTA has been applied to the study of causation probabilities of ship collisions. Figure 2-2 depicts the FT model used in (Friis-Hansen, 2008) for predicting the causation probability of a ship collision with fixed objects.

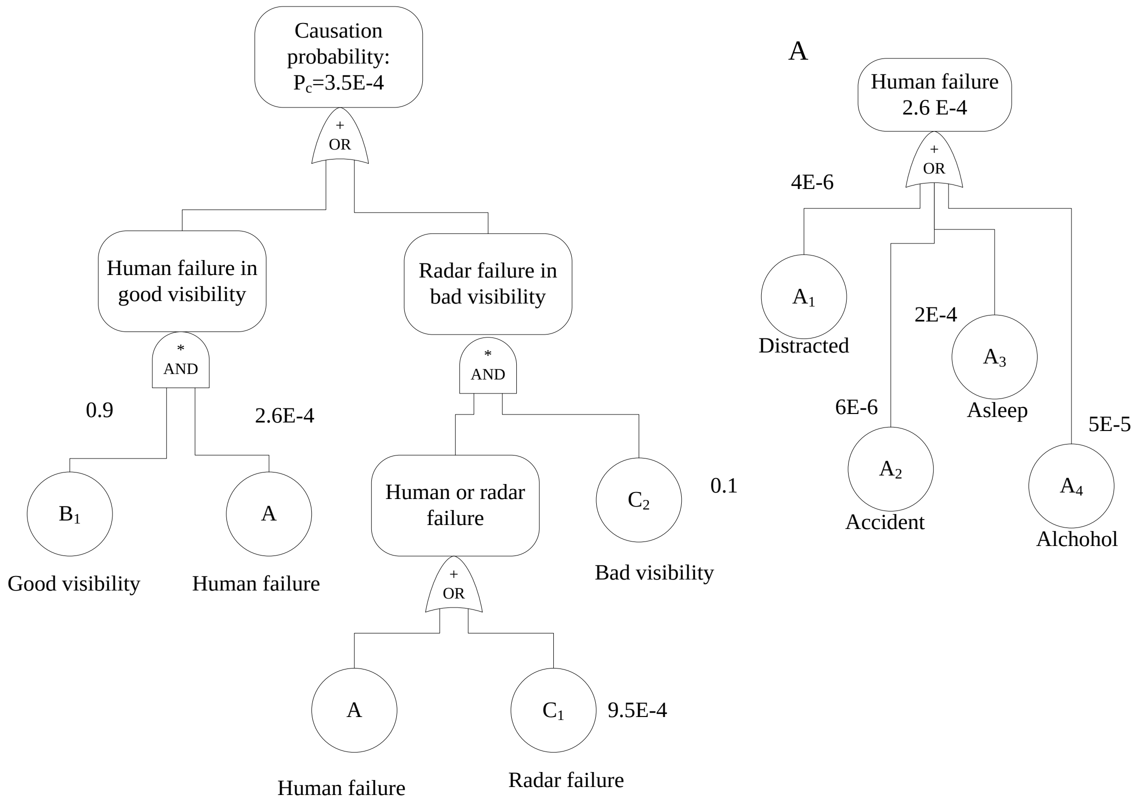


Figure 2-3 FT model developed by Friis-Hansen (2008) to estimate the causation probability for collision with fixed objects

Similarly, Figure 2-4 shows the FT model established in (Fowler & Sørgård, 2000) for modelling the causation probability of ship-to-ship collisions under good visibility situation while on dangerous courses.

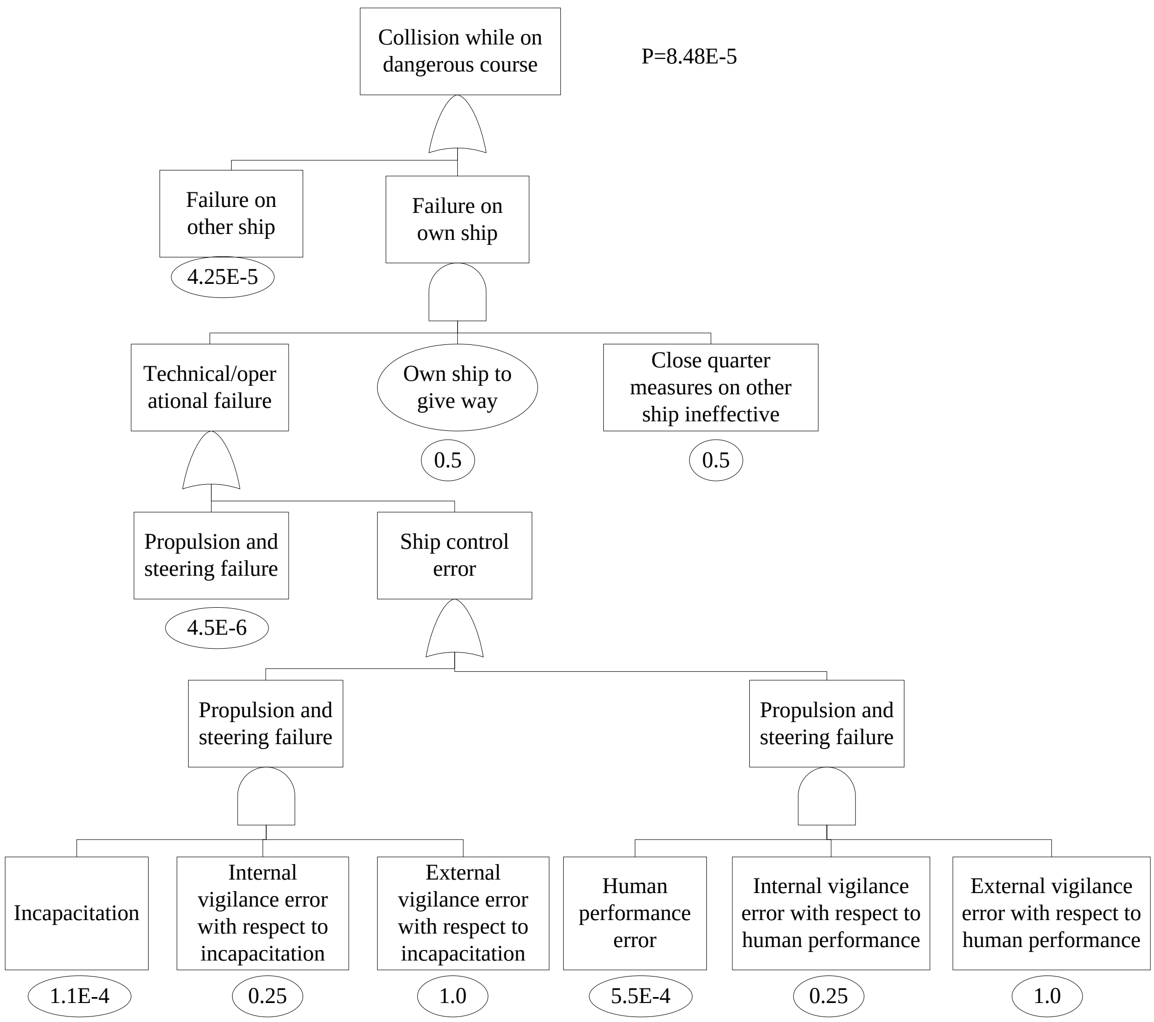


Figure 2-4 FT model developed by Fowler and Sørgård (2000) for the causation probability of ship-ship collision under good visibility

Figure 2-5 is another model used for collision causation probability of two ships in close quarters (Pietrzykowski, 2007). Collision was modelled as a result of deviations in either ship's courses. The course deviation event was further developed to events such as the "error of collision situation identification" and "error of preventive manoeuvre performance".

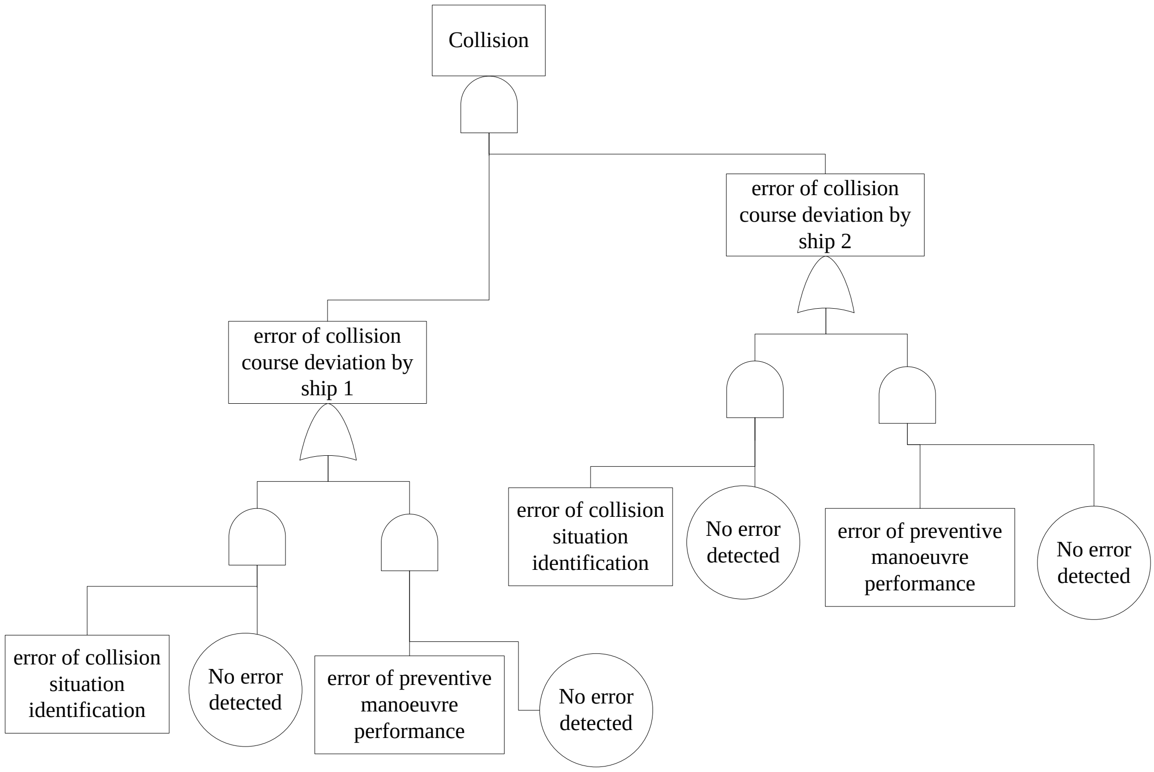


Figure 2-5 FT model developed by Pietrzykowski (2007) for ship-ship collisions

More applications of FTA for collision causation probability prediction with different levels of model complexities could be found in (Antao & Soares, 2006) (Martins & Maturana, 2010) (Uğurlu et al., 2013).

Another popular method for causation probability modelling is the BN method. Many BN models for collision causuation probability analysis can be found in the literature. As early as the late 1990s, BN was applied for the causation probability prediction for ship-to-ship collisions in the Increased Safety and Efficiency in Ship Design and Operation (ISESO) project, as shown in Figure 2-6. The model was also employed in the software Grounding and Collision Analysis Toolbox GRACAT.

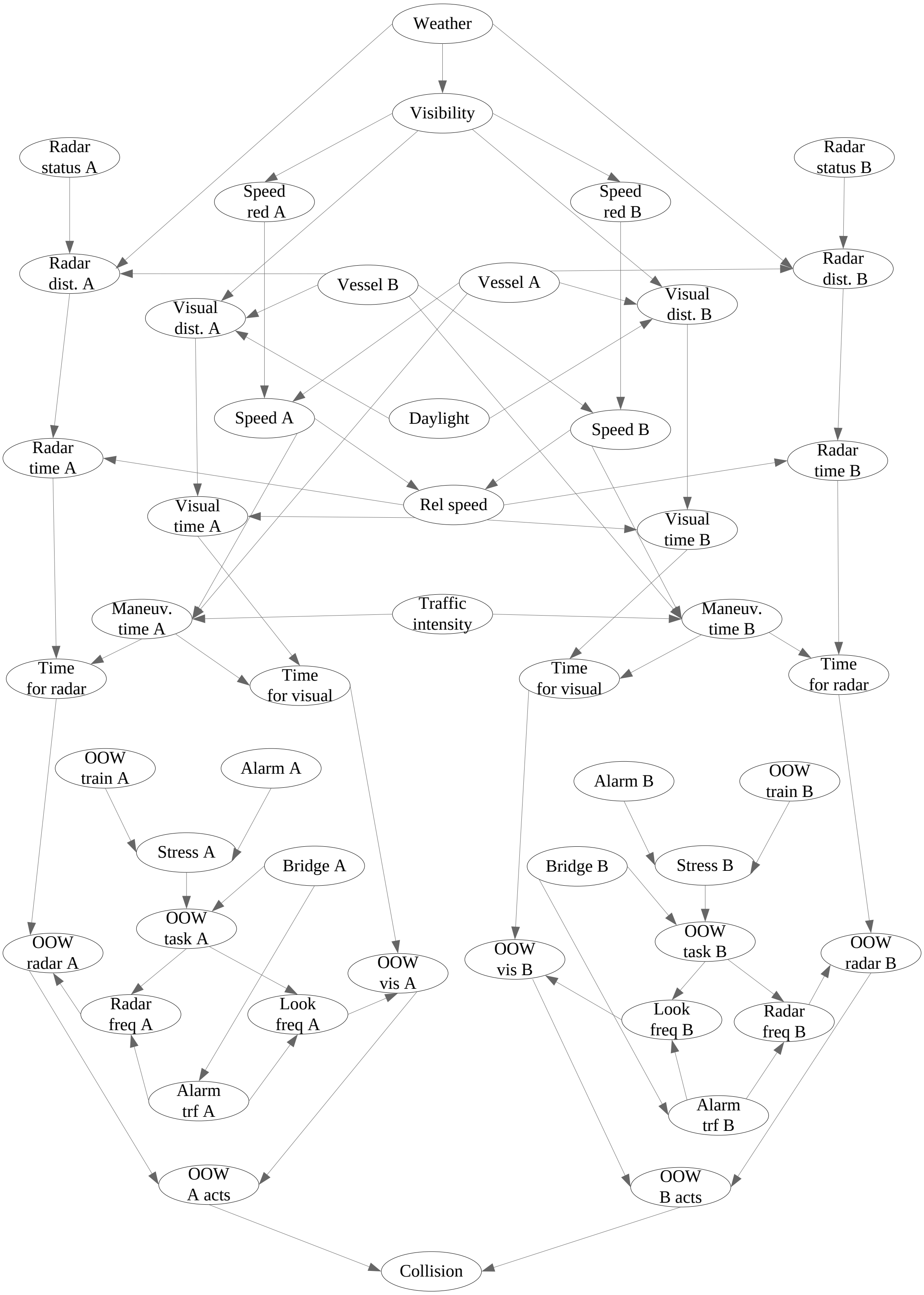


Figure 2-6 BN model for causation probability for ship-ship collision used in GRACAT

Source (Friis-Hansen & Simonsen, 2002)

One of the most comprehensive causation models is the BN model developed in (Det Norske Veritas, 2003), where causal relations among more than 60 variables were captured. It covered factors such as working conditions (e.g. bridge design, hours on watch, distractions, weather and visibility), personal factors (e.g. tiredness and stress level) and management factors (e.g. training and passage planning). An illustration of the simplified model can be found in Figure 2-7. This model has been applied directly or in a modified manner in many other studies, such as (Hänninen & Kujala, 2009) (Hänninen & Kujala, 2012) (Hänninen, Kujala, Ylitalo, & Kuronen, 2012).

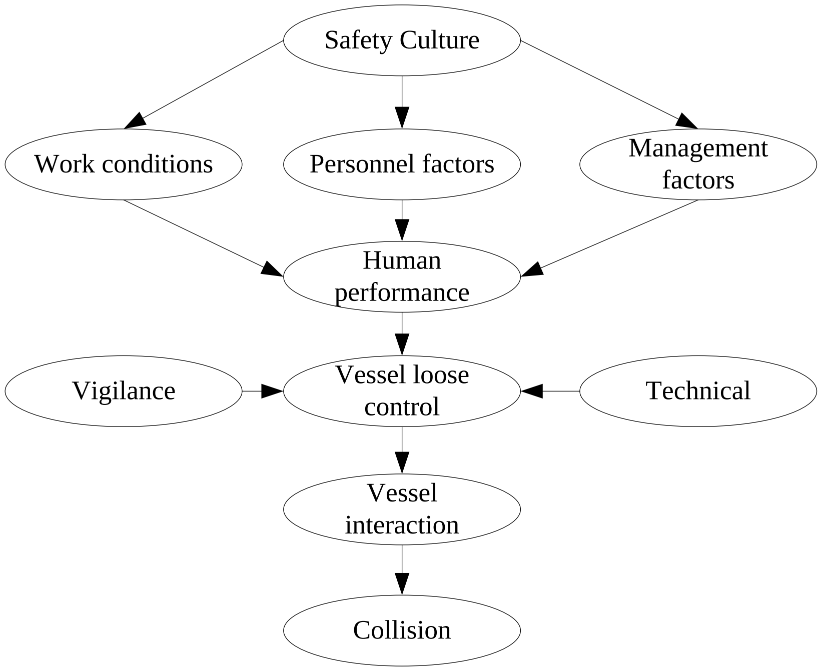


Figure 2-7 Simplified BN model for ship collision causation probability developed in (Det Norske Veritas, 2003)

Based on the Det Norske Veritas (DNV) model described above, a similar BN model was developed to evaluate the effect of implementing an Enhanced Navigation Support Information (ENSI) navigation service on the collision causation probability (Hänninen et al., 2013), as shown in Figure 2-8.

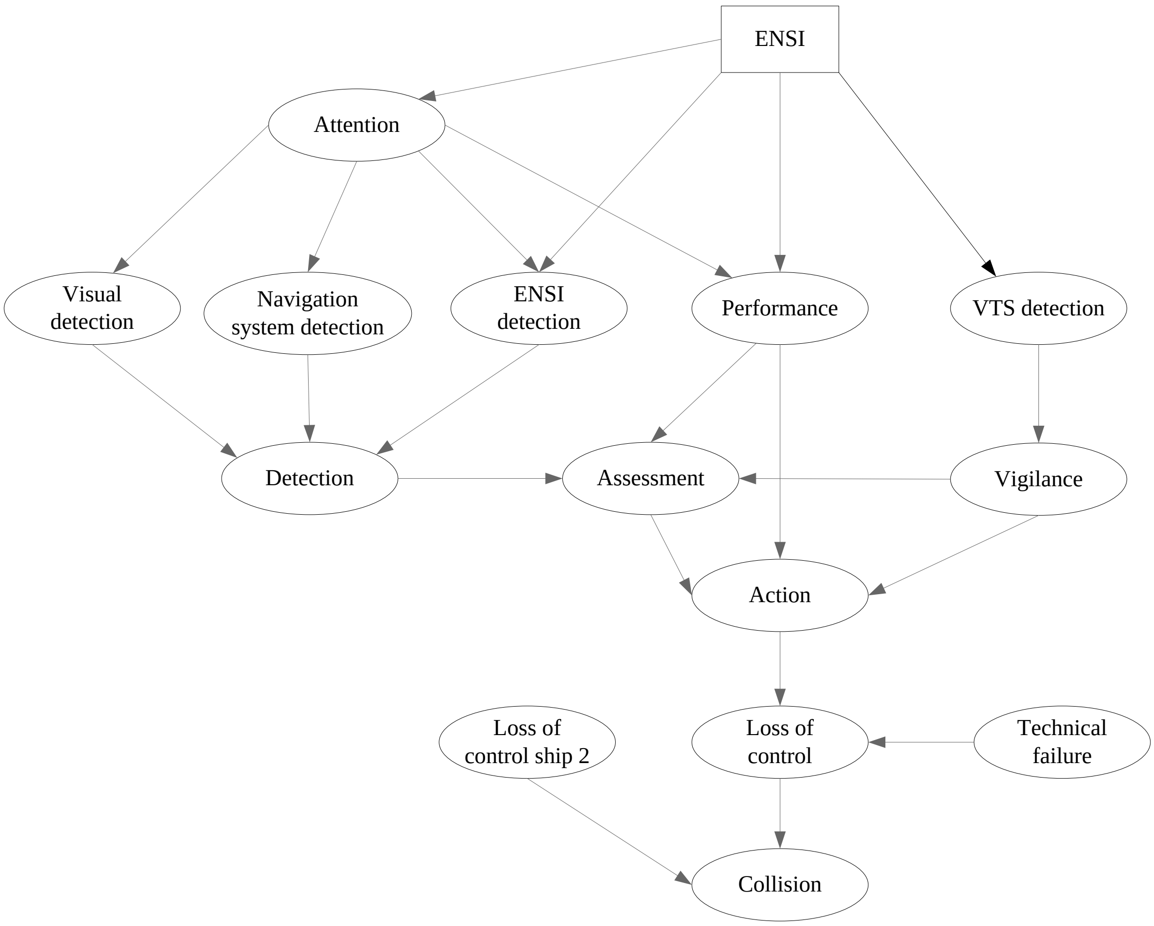


Figure 2-8 Simplified BN model to evaluate the effects of ENSI navigation service on ship collision causation probability developed by (Hänninen et al., 2013)

FTA shares many common features with BN and FTA models can be easily converted into BN models, but not the other way round (Khakzad et al., 2011) (Khakzad, Khan, & Amyotte, 2013). The integration of BN and FT methods has been applied to the study of collision risk for High Speed Craft (HSC) (Trucco et al., 2008). Compared to FTA, BN has the advantage of dealing with common factors, using multi-state variables and enjoying more flexibility in model construction. Therefore, BN would be adopted as the methodology in this study. However, there are also challenges with BN modelling, especially the parameterization step. Detailed discussion on the benefits and challenges of BN applications for maritime accident modelling can be found in Section 3.2.

2.1.2 Quantitative risk assessment framework for ship collisions: the one-step method

Some studies modelled collision using the one step method, and did not differentiate between geometrical probability and causation probability. Related applications could be found in (Y. F. Wang, Roohi, Hu, & Xie, 2010) (Y. F. Wang, Xie, Chin, & Fu, 2013) (Jun Ren, Jenkinson, Wang, Xu, & Yang, 2008) (Akhtar & Utne, 2014). Figure 2-9 shows the one step model developed in (J Ren, Wang, & Jenkinson, 2005) (J Ren, Wang, Jenkinson, Xu, & Yang, 2007) (J Ren, Jenkinson, Wang, Xu, & Yang, 2009) for the probabilistic analysis of ship collision with FPSO.

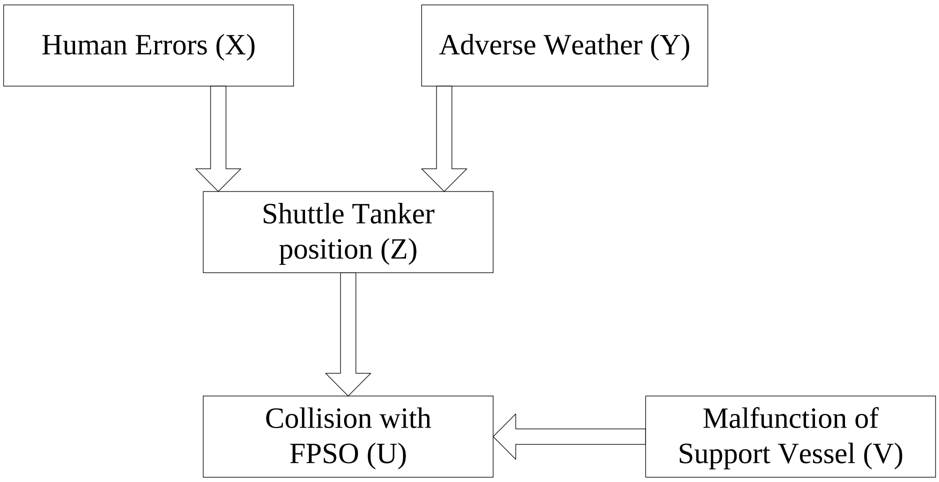


Figure 2-9 The one step model for collision with FPSO used in (J Ren et al., 2005) (J Ren et al., 2007) (J Ren et al., 2009)

Figure 2-10 shows another example of the one step model used in (Y. F. Wang et al., 2010).

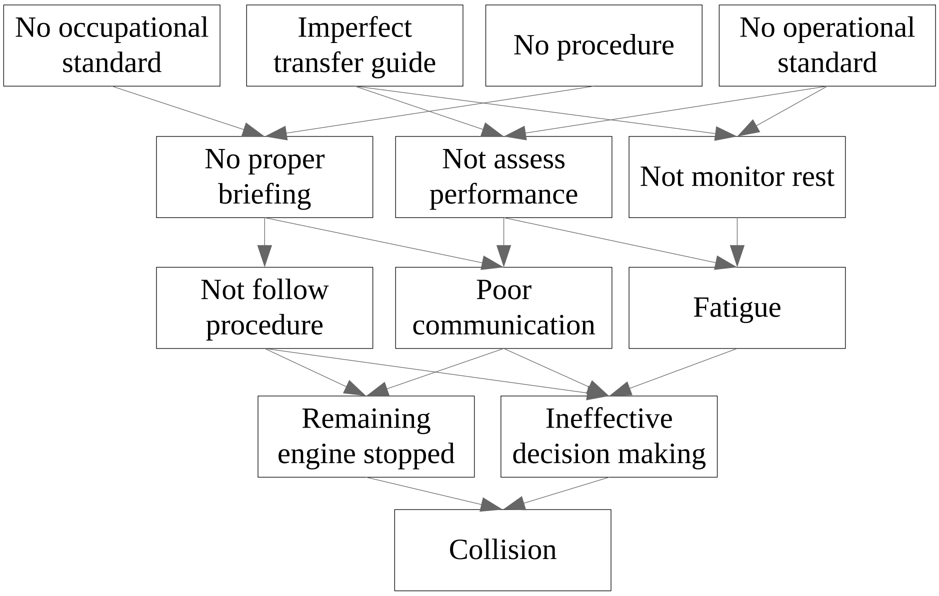


Figure 2-10 The one step model of ship-ship collision developed by Y. F. Wang et al. (2010)

2.2 Review of occupational accidents and injuries of seafarers

2.2.1 Qualitative and simple quantitative studies with descriptive statistics

Some qualitative analyses have been conducted on seafarers' occupational accidents and injuries through field interviews with front line seafarers (Borovnik, 2011), review of literature (Grøn & Knudsen, 2012) and consultation of maritime experts' opinions (Oldenburg, Baur, & Schlaich, 2010). For example, Borovnik (2011) conducted field interviews with 40 seafarers from Kiribati and 19 seafarers from Tuvalu, and revealed the challenging working conditions such as long contracts and lengthy working period for seafarers from developing countries in the two Asian Pacific islands.

There have been a few quantitative studies, where descriptive statistics were applied to analysis of the historical workplace accident records to find the injury pattern (Ellis, Bloor, & Sampson, 2010) to develop preventative legislation schemes (Rodriguez & Formoso, 2007). Differences in risk perceptions on job-related tasks were analysed using summary percentages of the survey data in (Bailey, Ellis, & Sampson, 2007), which were compared with statistics from the actual accident recordings (Bailey, Ellis, & Sampson, 2010). Two way contingency tables and Chi-square tests were the main methodologies applied in the study by HSE (2000) to analyse the injury records. Multivariate analysis, in particular the log linear method with Poisson errors, was conducted when three or more variables were included.

Incidence rate (IR) and incident rate ratio (IRR) were the most widely used indexes to analyse seafarer injuries. IR is the number of injuries related to the number of workers (Rodriguez & Formoso, 2007) or working hours (Olaf C Jensen et al., 2004) during a specific period. IRR is the ratio between two incident rates, i.e. IR_1/IR_2 (Olaf C Jensen et al., 2004). Normally, the exact IR is difficult to obtain due to uncertainties in the denominator. However, by comparing IRR, groups with relatively high injury risks can be identified. To reduce the confounding effects, the crude ratios are often adjusted with multiple regression methods.

For example, in (Olaf C Jensen et al., 2004) and (Olaf Chresten Jensen, JFL Sørensen, et al., 2004), IRRs and adjusted IRRs with multiple Poisson regression were used to analyse the data on self-reported occupational injuries of seafarers collected from a survey. Younger seafarers (less than 35 years old) were identified to bear higher risks compared to the elder group with an IRR value of 2.11. Meanwhile, the non-officers were found to be more prone to injury risks than the officers with an IRR value of 1.57. In (Jensen, 2009), the higher IRR revealed two higher risk groups, i.e. seafarers in fair health condition and seafarers who do not use personal protection device. In (H. L. Hansen, Laursen, Frydberg, & Kristensen, 2008), IR and IRR were used to study the influence of seafarers' nationalities on occupational accidents. Seafarers from Philippines were found to have lower occupational risks compared to Europeans (both western and eastern Europeans). Adjusted relative risk with Poisson regression was used for analysing the non-fatal injuries aboard merchant ships regarding to vessel type, seafarers' position, age, time on board, change of ship since last employment period, and nationality (H. Hansen, Nielsen, & Frydenberg, 2002).

Similarly, odds ratio and adjusted odds ratio with multiple logistic regression were used as measures to analyse the seafarers' non-fatal injuries related to slip, trip and fall (Jensen et al., 2005). Odds ratio and adjusted odds ratio with logistic regression were used for evaluating injury risk factors in (Martinovich, 2013) where age and experience were found to be important factors.

Two biggest limitations for the descriptive statistics are the number of variables that can be studied simultaneously and the restrictions on the complexity of relationship to model. Considering the complicated causal relations for the study of occupational accidents and injuries, advanced models are needed which can deal with large-scale data both in terms of data quantity and dimension, learn non-linear relationships, and have good predictive as well as interpretative potentials (Rivas et al., 2011).

2.2.2 Classification of occupational accidents using data mining techniques

In recent years, with the development of computer capacity and information explosion, the application of advanced data mining techniques has benefited many fields including finance, medicine and engineering. Data mining is a discipline combining the knowledge of statistics, decision making, machine learning, artificial intelligence as well as database. Data mining methods could partially overcome the drawbacks with descriptive statistics stated in Section 2.2.1. In the literature, many data mining techniques, such as neural network, classification trees and association rules have been used for the analysis of occupational accidents and injuries in many sectors, as summarized in Table 2-2.

Table 2-2 Application of data mining techniques for analysis of occupational accidents and injuries

Articles	Data source	Methodology	Output variable
(Matías, Rivas, Martín, & Taboada, 2008)	148 falls at workplace for 1500 companies from 2003–2006	1. CT; 2. SVM; 3. ELM; 4.BN	Fall Type: 1. Floor-level fall 2. 2. other falls
(Maurizio Bevilacqua, Ciarapica, & Giacchetta, 2010)	400 occupational accidents recorded from 1997–2007 in API refinery	1. NBR; 2. CHAID;3. Exhaustive CHAID; 4. CART; 5. QUEST, 6. ANN 7. Neuro-Fuzzy	Risk index: 1. Low risk (<4), 2. Medium risk (<10), 3. High risk (>10)
(M Bevilacqua, Ciarapica, & Giacchetta, 2008)	200 plus occupational accidents occurred in the decade 1994–2004 at API refinery	1.CHAID; 2. Exhaustive CHAID; 3. CART; 4. QUEST	Risk index: (Same as above) Type of accident (11 categories) Period [1994–1997] [1998–2001] [2002–2004]
(Cheng, Lin, & Leu, 2010) (Cheng, Leu, Cheng, Wu, & Lin, 2012)	1347 (1542) accident cases during the period 2000–2007 (2009)	1. Chi-square test and Cramer's statistic; 2. Online analytical processing (OLAP); 3. Association-rule; 4. CART	Accident type 1. Falls/tumbles 2. Collapse of object 3. Struck by Electric shock 4. Falling object 5. Traffic accident 6. Other
(Rivas et al., 2011)	62 occupational accidents and incident reports collected between Sep 2007 and Mar 2008	1. Decision rules; 2. BN; 3. SVM; 4. CT; 5. LR	Event (EVT): 1. Accident (A), 2. Incident (I)
(Shankar Beriha, Patnaik, & Shankar Mahapatra, 2012)	288 questionnaires from a survey about the perceptions on injury likelihood	ANN	Low probability of injury Strongly disagree to Strongly agree

Table 2-2 Application of data mining techniques for analysis of occupational accidents and injuries (continued)

Articles	Data source	Methodology	Output variable
(Dumrak, Mostafa, Kamardeen, & Rameezdeen, 2013)	24,764 construction accidents reported during 2002-2011 in South Australia	Chi-square test	Injury severity 1.Minor 2.Moderate 3. Serious 4. Severe 5. Critical 6. Fatal
(Nenonen, 2013)	Slipping, stumbling, and falling (SSF) during 2006 and 2007	1. Decision tree; 2. Association Rules	Type of accident: 1. SSF 2. other accidents
(Verma, Khan, Maiti, & Krishna, 2014)	843 incidents occurred in a steel plant in India from March 2010 to July 2013	Association rules	Incident type 1. Injury 2. Near miss 3. Property damage
(Fragiadakis, Tsoukalas, & Papazoglou, 2014)	294 reports of Occupational Accidents in four ship repair yards from 1989 to 2008	ANFIS	Occupational risk (Gravity Factor values)
(Sanmiquel, Rossell, & Vintró, 2015)	69,869 instances of occupational accidents in the Spanish mining sector from 2003–2012	1. Classification tree; 2. Association-Rules; 3. Decision tree	Type of Accident (TA) (5 categories) Lost Work Days ([1, 9], [10, 29] [30, 59], [60+])
(Gerami, Bartashak, Rocky, & Honarmand, 2014)	2396 incidents occurred during the years 2011 to 2013	Multiple Linear regression	Injury (Type of accident) (16 categories)

CT: Classification trees; CART: classification and regression trees; SVM: support vector machines; ELM: extreme learning machines; ANN: Artificial Neural Network; BN: BN; NBR: Negative Binomial Regression; CHAID: Chi-Squared Automatic Interaction Detection; QUEST: Quick, Unbiased, Efficient Statistical Tree; LR: logistic regression

Among the literature above, accident and incident records or databases were the main data source for the respective studies. A few papers applied data selection process (Rivas et al., 2011) to identify the most relavant variables prior to the data mining analysis. In most studies, the data mining techniques were applied to forecast the class of accidents or incidents according to its type or severity, given that an occupational accident or injury had already happened. Therefore, only one dimension, i.e. the consequence of accidents and injuries was analysed. The likelihood of the accident occurrences was ignored. This is mainly due to the structure of accident databases, which only contain information on the accident occasions, the probability of which was 100%. Thus, it was not possible to predict the accident probabilities with such data unless the historical records were re-examined for the likelihood value, as in the cases of (M Bevilacqua et al., 2008) and (Fragiadakis et al., 2014), where a risk index or gravity value was re-calculated for the occupational accident records, taking into account both accident frequency and severity.

Compared to the historical accident databases, specially designed surveys allow more information to be collected, including both the accident cases and ordinary cases, thus enabling the probabilistic prediction of the injury occurrences. Moreover, through surveys, the conceptions on the injury risk levels can also be obtained, as in (Shankar Beriha et al., 2012). Methodology wise, BN stands out for its predictive and explanatory capacity while ANN is a black box with reasonable predicting capacity. Moreover, the probability concept in BN is suitable for representing uncertainty.

2.2.3 Occupational accident risk prediction models

There were also other quantitative models built through the quantification of experts' opinions for occupational risk evaluation utilizing methods such as Analytic Hierarchy Process (AHP), Fuzzy theory, reliability methods as well as BN.

McCauley-Bell and Badiru (1996a) (1996b) applied AHP to derive the weights of different risk factors (e.g. task related, personal and organizational factors) for occupational risks through paired comparisons. Fuzzy theory was used subsequently to calculate the overall risk levels, depending on the values of individual risk factors and the corresponding weights.

Daryl Attwood, Faisal Khan, and Brian Veitch (2006) developed a multilevel model to predict the expected number of occupational accidents over a period in the oil and gas industry. Various influencing factors including external factors, organizational factors and direct factors were included in the model, identified from a detailed literature review. The accident occurrence was regarded as a type of system failure, and thus the probability was calculated based on the system reliability methods (D Attwood, F Khan, & B Veitch, 2006).

T.-T. Chen and Leu (2014), and Leu and Chang (2013) transferred the FT model for falling risk assessment in construction projects to a BN model, which overcame the incapability of FT in modelling interdependency. Expert knowledge was used for adding supplementary structural relations as well as defining the conditional probability tables. In (J. E. Martin, Rivas, Matías, Taboada, & Argüelles, 2009), two separate BN models were built with experts' prior knowledge for occupational accidents in construction projects: one for accidents related to ladder-based tasks and the other for accidents related to tasks performed on scaffolding, platforms, structures and other auxiliary equipment. Parameters of these two models were learnt through a survey. The BN models built in this way combined both the experts' knowledge and evidence from empirical data.

2.3 Addressing the gaps of literature

2.3.1 Study on the ship collision accidents

The most popular method for ship collision modelling is the two-step method where the collision probability is modelled as the product of geometrical probability and causation probability. Many models have been developed for both geometrical probability and causation probability modelling respectively. For applications, simplifications of the detailed models can be adopted depending on the purpose of modelling. For collision frequency estimation for a specific geographic location, i.e. risk mapping of the region, detailed geometrical models are often needed while simplified causation probability numbers are used. On the other hand, for accident management purpose, especially evaluation of the risk control measures, detailed causation models dealing with accident causal relations are essential. This study focuses on the latter.

Due to its good properties, the BN method was recommended by IMO for the risk assessment of maritime accidents. Many collision causation probability models have been developed with BN. Through the review of literature, it was found that experts' opinion is the main data source for most BN models, due to the scarcity of historical data for rare accidents like ship collisions. This poses a great challenge for the experts, since they are not typically asked about their expertise during the probability elicitation process, but about the probability of other people or system's failures. Hence, the judgement provided by the experts may not be accurate (Brooker, 2011). Moreover, the huge number of conditional probabilities to elicit also increases the possibility of inconsistency. The epistemic uncertainty in maritime accidents modelling when experts' opinions are involved, reflected as the uncertainty about model parameters, has been well recognized but seldom discussed. One exception was (O.-V. E. Sormunen et al., 2014), where the uncertainty levels associated with different parts of the chemical tanker collision model were analysed with qualitative terms, i.e. "Low" "Medium" "High".

Therefore, this study aims to improve this gap and explore the extension of the traditional BN method with imprecise (interval) probabilities to address the epistemic uncertainty when experts' opinions are employed as the data source for modelling, especially for the LP-HC accidents. Detailed discussions can be found in Chapter 4.

2.3.2 Study on the occupational accidents and injuries of seafarers

Many of the existing studies on seafarer's occupational accidents and injuries adopted either qualitative method through literature analysis and field interviews, or simple quantitative methods using descriptive statistics in the form of indexes. Regression methods have also been applied in some studies. However, the simple quantitative analyses restrict both the number of variables and the complexity of relationship in modelling. The application of data mining techniques such as neural network, classification trees, association rules and BN, can potentially deal with large-scale data in terms of both data quantity and dimension, as well as learn non-linear relationships. Among them, BN method stands out for its interpretive power as well as predictive capacity, while neural network works as a black box and lacks interpretive transparency. These advanced quantitative methods have been applied for the study of occupational accidents in many other sectors (e.g. construction industry). So far, however, no such studies exist on studies of seafarers' occupational accidents and injuries. On the other hand, the advanced data mining techniques were applied mostly for the classification of existing accidents per their severity, constrained by the nature of data sources such as historical accident/incident reports, records and databases. In addition, the previous studies on seafarer's occupational injuries are too simplistic, covering only objective risk factors and ignoring the human and organizational factors, which account for a higher proportion of the causes of injuries, while the risk assessment methods should be able to (Rivas et al., 2011):

- Deal with large-scale data, in terms of both quantity and dimension
- Learn non-linear relationships
- Have good predictive as well as good interpretative potentials.

This study aims to improve the gaps by conducting an extensive empirical survey on various potential risk factors, including the seafarer's personal factors, behavioral safety routine and organizational management practices. Based on the survey data, a BN model is built for the probabilistic modelling of seafarer’s injuries with predictive indicators. More details of the study are elaborated in Chapter 5.

3.1 Bayesian Network (BN)

3.1.1 Definition of the BN method

Bayesian Network, often known as BN for short, belongs to the family of Directed Acyclic Graphs (DAGs). A BN can be defined as follows:

A BN over a set of variables $\boldsymbol{X}=\{X_0, X_1, \ldots X_k\}$ *is a pair* $\langle \zeta, \mathbb{P} \rangle$ *such that* $\mathbb{P}$ *is a set of conditional mass functions* $P(X_i|\pi_i)$*, one for each* $X_i \in \boldsymbol{X}$ *and* π_i *denotes the parent nodes for the variable* X_i*.*

The graph ζ is a compact representation of conditional independence among the variables in $\boldsymbol{X}$. Under the Markov condition, i.e. each variable is independent of its non-descendant non-parents conditional on its parents, the conditional probability mass functions associated to the specification of the Bayesian network can be employed to specify a joint mass function by the following formula (Antonucci, Sun, de Campos, & Zaffalon, 2010).

$$\mathrm{P}(\mathbf{x})=\prod_{i=0}^{n} P(x_i|\pi_i) \tag{3-1}$$

where $\mathbf{x} \in \Omega_X$ *, and for each i=1,2,…n, the values of* (x_i, π_i) are those consistent with $\mathbf{x}$. $\mathrm{P}(x_i|\pi_i)$ is the conditional probability for $X_i = x_i$.

3.1.2 BN specification

The application of BN includes two parts: the qualitative part for developing the model topology, and the quantitative part for defining the model parameters. In practice, both the structure and the parameters can be obtained using subjective judgments from domain experts or learnt with relative data (Koski & Noble, 2011). Specifying the parameters, i.e.

conditional probabilities, for a BN model is one of the most challenging tasks in applications.

Depending on the type of the nodes in a BN, the conditional probability distribution may take different forms. For discrete nodes, the condition probabilities for each node could be arranged in a table, called Conditional Probability Table (CPT). The specification of conditional probability distribution for the continuous nodes is much more complicated.

A special case is the Conditional Linear Gaussian (CLG) BN, which consists of a combination of discrete variables and continuous variables, with the restriction that discrete nodes cannot have continuous nodes as parents (Kjærulff & Madsen, 2006) (Kjrćulff & Madsen, 2013). The conditional probability distribution for a CLG node X, could be specified as $L(\mathrm{X} \mid Z=z, I=i)=\mathbb{N}(\mathrm{A}(i)+\mathrm{B}(i)^{\mathrm{T}} \mathrm{z}, \mathrm{C}(i))$, where A is a table of mean values (one value for each configuration *i* of the discrete parent variables I), B is a table of regression coefficient vectors (one vector for each configuration *i* of I with one regression coefficient for each continuous parent variable), and C is a table of variances (one value for each configuration *i*).

BN with discrete nodes is more widely used than BN with continuous nodes, due to the complexities in parametrization and computation with the latter. In practice, continuous nodes are always discretized. However, the probability specification for discrete BNs is also challenging considering the large number of CPTs to define. For a node with *i* states and *k* parent nodes (*n* states each node), the number of conditional probability values to specify is $i \times n^k$ (Knochenhauer et al., 2013). Discussions on how to reduce the number of CPT entries (Achumba, Azzi, Ezebili, & Bersch, 2013) and obtain reliable individual conditional probabilities are provided in Section 3.2.3, especially when expert opinions are the main data source.

3.1.3 BN updates

In BN, making queries of some nodes given the observation of other nodes is called probability updates, as illustrated in Figure 3-1. The left side of the figure shows the prior probabilities for the famous ‘wet grass’ BN model, while the right side shows the updated BN with the evidence “Rain=True”.

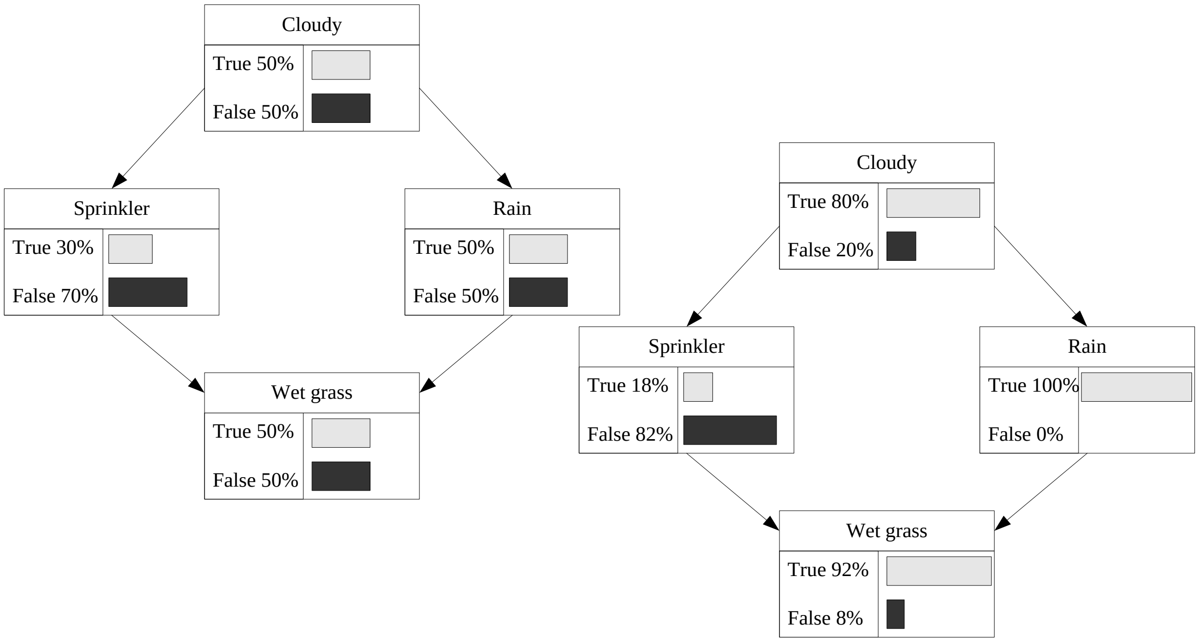


Figure 3-1 Example of probability updating with evidence in BN

Source (author)

The posterior probabilities for a queried node X_q can be computed using the following function.

$$\mathrm{P}(\mathbf{x})= P(x_q | x_E) = \frac{\sum_{x_M} \prod_{i=1}^{n} P(x_i | \pi_i)}{\sum_{x_M, x_q} \prod_{i=1}^{n} P(x_i | \pi_i)} \tag{3-2}$$

where $X_E = x_e$ refers to the evidence nodes, and X_M denotes the remaining nodes, i.e. $X_M = X \backslash (X_q, X_e)$.

The evaluation of function 3-1 was proved to be Non-deterministic Polynomial (NP) hard (Cooper, 1990). But for polytrees, the Pearl's algorithm allows efficient belief updating. For a generic node X, whose parent nodes are U= {U_1, U_2, … U_n} and children nodes are Y={Y_1, Y_2, … Y_m}, as shown in Figure 3-2, the probability *P[X|e]* for all nodes can be computed through functions 3-3 to 3-7:

$$P[X|e] = \alpha\pi(X)\lambda(X) \tag{3-3}$$

$$\pi(X) = \sum_U P[X|U]\prod_i \pi_X(U_i) \tag{3-4}$$

$$\lambda(X) = \prod_j \lambda_{Y_j}(X) \tag{3-5}$$

$$\pi_{Y_j}(X) = \pi(X)\prod_{k \neq j} \lambda_{Y_k}(X) \tag{3-6}$$

$$\lambda_X(U_i) = \beta\sum_X \lambda(X) \sum_{U_k \neq U_i} P[X|U]\prod_{k \neq i} \pi_X(U_k) \tag{3-7}$$

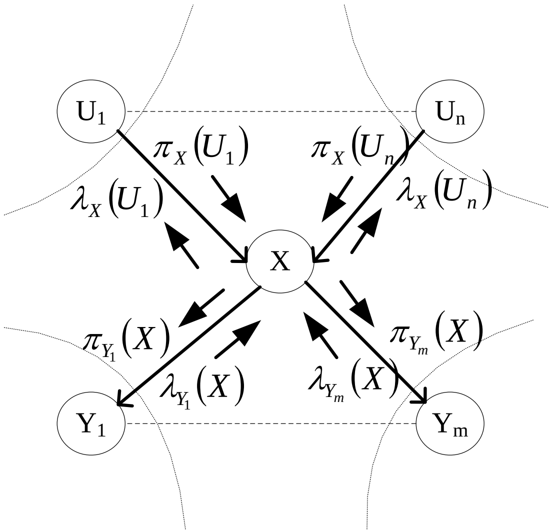


Figure 3-2 A fragment of singly connected BN net and its message passing

Source (Fagiuoli & Zaffalon, 1998)

The following assumptions were adopted: ①for the source node (node without parent nodes), $\pi(X)=P[X]$; ②for the barren node (node without children nodes), $\lambda(X)=1$; ③for an evidence node $X=x$, a dummy child node Y' was assumed, where $\lambda_{Y'}(X=x)=1$ and $\lambda_{Y'}(X \neq x)=0$. This method could be modified for belief updating of BN with interval probabilities by absorbing the constants α and β. More details can be found in Section 3.3.3.

3.1.4 Validation of BN models

Even though it is not easy to validate a BN model, especially for expert elicited BNs, it is not impossible. Methods such as verification by experts, comparison with similar studies and cross-validation with empirical data have been applied for BN validation purposes (Akhtar & Utne, 2014). In addition, sensitivity analyses, including sensitivity to parameters and sensitivity to findings, are also widely used for BN validations. The following subsections summarize some of the validation methods.

3.1.4.1 BN Validation framework

The main source of confidence for a BN model comes from the model structure, discretisation, parameterization as well as the model behaviour. Figure 3-3 shows a comprehensive validation framework, which was adapted from the psychometrics field by Pitchforth and Mengersen (2013), for BN validations especially for expert elicited BNs.

The validation framework proposed seven types of validity tests, i.e. nomological validity, face validity, content validity, concurrent validity, predictive validity, convergent validity, and discriminant validity, covering both qualitative and quantitative aspects. Interested readers can be directed to (Pitchforth & Mengersen, 2013) for more details. The framework has been partially applied for the validations of BN models in the maritime domain (Montewka et al., 2014) (Goerlandt & Montewka, 2014) (Hänninen & Kujala, 2014).

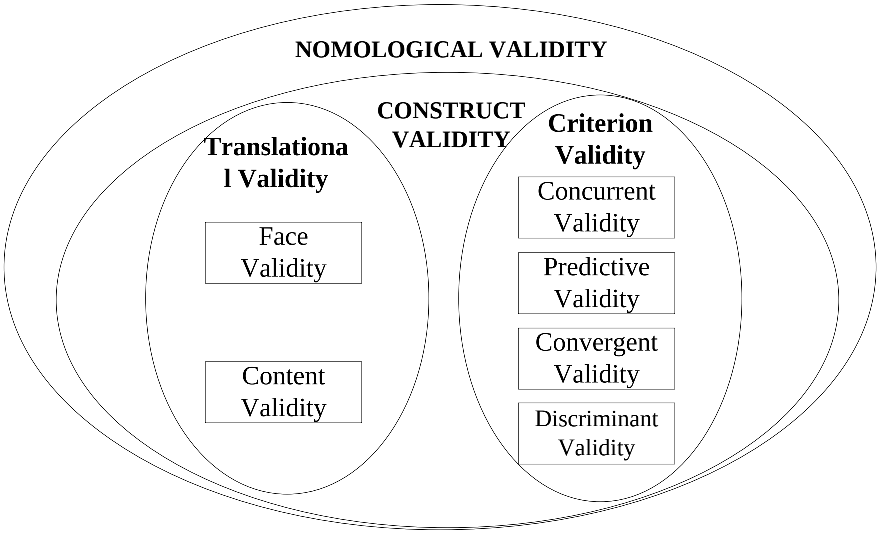


Figure 3-3 BN validation framework

Source (Pitchforth & Mengersen, 2013)

3.1.4.2 Sensitivity Analysis 1: Sensitivity to parameters

Sensitivity to parameters investigates the effects of inaccuracy in parameters on the model outputs. It can be examined through an empirical approach, i.e. to manually alter the parameters (conditional probabilities) one by one and monitor the changes of posterior probabilities of the target nodes (Woodberry, Nicholson, Korb, & Pollino, 2004). Assume that $x = P(y_j|\pi)$ is the parameter under study, where y_i is one state for the node Y and π is the combination states of Y's parent nodes. Under the rule of proportional covariation,

$$P(y_j|\pi)(x) = P(y_j|\pi) \cdot \frac{1-x}{1-P(y_i|\pi)} \tag{3-8}$$

where $P(y_j|\pi)$ is the parameter for any other state of Y under the same instantiation.

If no evidence is observed, any posterior probability relates linearly to any parameter (Van Der Gaag, Renooij, & Coupé, 2007).

$$\mathrm{P(B)} = C_1 x + C_2 \tag{3-9}$$

where C_1 is the sensitivity value) and C_2 is a constant. Therefore, the sensitivity value also equals to the difference in the posterior probability of the target node when the parameter x changes from zero and one (Hänninen & Kujala, 2012).

3.1.4.3 Sensitivity Analysis 2: Sensitivity to findings

Sensitivity to findings, also referred to as the value of information analysis, could be measured through the concept of entropy and mutual information (Pollino, Woodberry, Nicholson, Korb, & Hart, 2007). It has been widely used to complement the sensitivity to parameters analysis for BN validations (Hänninen & Kujala, 2012) (Montewka et al., 2014). The entropy H(X) of a variable X evaluates the randomness of X. H(X) is maximum when all states of X are equally likely. Mutual information I (X, Y) is the difference of entropy H(X) with and without observations on Y, as defined in the following functions.

$$H(X) = -\sum_{x} p(x) \lg p(x) \tag{3-10}$$

$$H(X|Y) = -\sum_{y} p(y) H(X|Y = y) \tag{3-11}$$

$$I(X,Y) = H(X) - H(X|Y) \tag{3-12}$$

where H(X) is the entropy of X without any observation, while H(X|Y) is the entropy of X with observations of Y. Mutual information measures the influence of knowledge on one factor on another. It also represents the degree of divergence of the joint probability P(X, Y) compared to the case if X and Y are independent. Particularly, I(X,Y) is equal to zero when X and Y are totally independent.

3.2 Benefits and challenges of BN for maritime risk modelling

3.2.1 Overview of the benefits and challenges of BN for maritime risk modelling

Some of the reasons to choose BN for maritime risk modelling are:

- Explicit presentation of causal relationships
- Both predictive and diagnostic inferences
- Combination of experts’ knowledge and empirical data
- Power to deal with uncertainty

- Updates with new information/observation.

The ability to model dependencies among events with probabilistic data makes BN suitable of risk analysis (Weber et al., 2012). As pointed out by Trucco and Leva (2012), the use of BN in modelling operational risks provides a special advantage over many other approaches, since BN is the knowledge representation of the domain and can explicitly include probabilistic dependence among the main elements and their causal relationships. Meanwhile, the ability of BN to make use of the experts' knowledge is very valuable for maritime risk modelling considering the data scarcity in the maritime domain. The above features also enable the incorporation of human and organizational factors in modelling, which account for most maritime accidents, bear high interdependencies and are difficult to obtain relevant data. The benefits of applying BN for maritime accident management and prevention are "its capacity to deal with complex systems", "partially addressing uncertainty through probability numbers", "relaxation of causality", "versatility which enables query on any variable", "dynamic modelling" and "the possibility of extension to a decision problem" (Hänninen, 2014).

The common challenges for BN applications include the difficulty in defining the related parameters, discretizing continuous variables, collecting and structuring the expert knowledge (Uusitalo, 2007). As to maritime accidents applications, "incomplete understanding of safety and accident occurrence", "scarce data", "data quality", "relying on experts" and "difficulties in model validation" were cited as the main challenges (Hänninen, 2014). In the following subsections, a general review on the main data sources for BN modelling in the maritime sectors as well as a detailed discussion on the challenges with probability elicitations are provided.

3.2.2 Data sources for BN modelling in maritime applications

There are three ways to build a BN: manually eliciting, automatically learning or a combination of both (Neil et al., 2000), i.e. to elicit both the structure and parameters of the network, to learn both the structure and the parameters through related data, or to apply the elicitation and learning algorithm respectively (Kjrǽulff & Madsen, 2013). The probabilities elicited from the domain experts are called subjective probabilities. When multiple experts are involved, elicitation could be conducted either individually or through group discussions (T. G. Martin et al., 2012). Experts elicited BN models may carry biases and uncertainties, while data-driven BN is considered to be more objective, supported with empirical data (Arsham, Edvard, Noora, Jakub, & Pentti, 2013).

The application of data-driven BN for maritime safety modelling was explored only in recent years. In some cases, the BN model structure was elicited while the conditional probabilities were learnt from relative data, see (K. X. Li, Yin, Bang, Yang, & Wang, 2014) (K. Li, Yin, Yang, & Wang, 2010) (Akhtar & Utne, 2014). In other cases, both the structure and the parameters were learnt from data, e.g. (Kelangath, Das, Quigley, & Hirdaris, 2012) (Arsham et al., 2013) (Hanninen, Sladojevic, Tirunagari, & Kujala, 2013) (Hänninen & Kujala, 2014). However, even though the data-driven BN method is promising, the accuracy of the learnt model remain great concern due to the availability and quality of related data.

Some papers used the ship damage database (Kelangath et al., 2012) or casualty database in combination with the ship information dataset and port state control inspection database (K. X. Li et al., 2014) (Hänninen & Kujala, 2014). The advantage of these databases is that they provide a relatively large quantity of data set compared to accident reports, which are mostly detailed long narratives for major accidents. However, one critical disadvantage is that most factors recorded in the mentioned databases are static factors such as ship age, ship size and so on, while information on human and organizational factors are normally not recorded. In addition, different databases are sometimes incompatible for integration (Hänninen & Kujala, 2014).

Accident reports were the data source for the study of (Akhtar & Utne, 2014) (Arsham et al., 2013) and (Hanninen et al., 2013). They contained detailed causal relationship, but the pre-processing or codifying of the long text narratives was time consuming and limited in quantity as well. In (Akhtar & Utne, 2014), the BN model had 46 variables but only 93 accidents were used for the parameter learning. In (Arsham et al., 2013) and (Hanninen et al., 2013), the BN model had 35 variables and 38 variables respectively, while the number of accident reports used for the structure and parameter learning were 73 and 143 only. The scarity of data is understandable considering the nature of rare accidents. However, with the limited small number of input data sets, the reliability of the learnt model is highly uncertain. In addition, comparisons showed that the performance of different BN structure learning algorithms varied a lot (Arsham et al., 2013) (Kelangath et al., 2012). Therefore, even though the data-driven BN is a promising method, its application is still constrained by the availability and quality of relevant data. Expert elicitation continues to play a very important role for the BN modelling of maritime accident risk assessment.

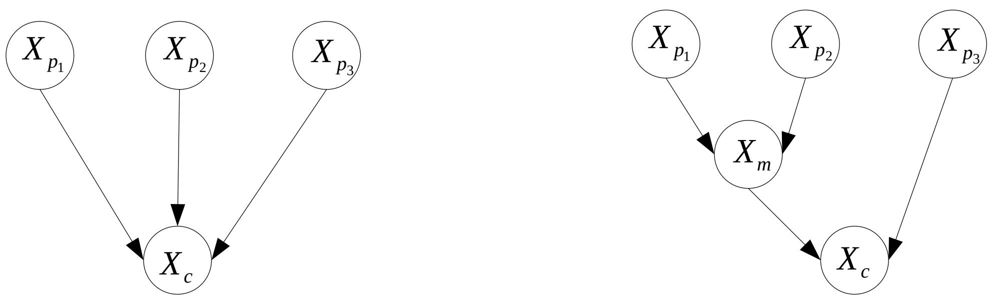
3.2.3 Challenges with expert elicitation in BN application

Probability elicitation from the domain experts is a challenging task. First, the design of the elicitation process itself, including the determination of experts and choice of elicitation techniques, might be a daunting process (Kuhnert, Martin, & Griffiths, 2010). Moreover, the demand of many conditional probabilities not only puts great workload on the experts but also poses challenges to the quality or consistency of the elicited result.

The elicitation process could be improved in two aspects: one is to reduce the burden of experts by reducing the number of conditional probabilities to elicit; the other is to facilitate the elicitation of individual probability (Knochenhauer et al., 2013). The following subsections review the techniques regarding these two aspects.

3.2.3.1 Reducing the number of conditional probabilities to elicit

One way to reduce CPT numbers is to simplify the model structure through nodes divorcing. The number of parent nodes could be reduced by introducing a mediating node, which in turn reduces the number of probability entries, since for a node with *i* states and *k* parent nodes where each parent node has *n* states, the number of conditional probabilities to define is $i \times n^k$ (Knochenhauer et al., 2013). Take the example in Figure 3-4a, if node X_c has four states ($i=4$), three parent nodes ($k=3$) and each parent node has four states ($n=4$), then 256 ($i \times n^k = 4 \times 4^3$) conditional probability numbers are to be specified. Nevertheless, if a mediating node X_m (also 4 states) is introduced (Figure 3-4b), both X_m and X_c now require only 64 conditional probability numbers. The total number of entries is thus 128 in total, reduced by half compared to the original 256.



(a) Original (b) Divorced

Figure 3-4 Nodes divorcing

Source (Knochenhauer et al., 2013)

Another option is to exploit the causal independence between the parent nodes through the application of the noisy-OR rule (binary nodes) or the noisy-MAX rule (nominal nodes), if the model satisfies the accountability and expectation independence requirement. The noisy-OR and noisy-MAX rule could considerably reduce the number of CPT entries. For a node *Y* with n_y states and *n* parent nodes, if the parent node *I* has n_{X_i} states, then the total number of parameters to elicit by the model builder using Noisy-

MAX will be $N = \sum_{i=1}^{n} \left(n_{X_i} - 1 \right) n_Y$ (Kraaijeveld, 2005), which is much less than the original $N = n_Y \prod_{i=1}^{n} n_{X_i}$. The Noisy-Max rule was applied for probability specification in the BN modelling for ship groundings in (Akhtar & Utne, 2014).

It is also possible to obtain a full CPT from a few elicited probabilities. Three methods were used in the rapid source term project (Knochenhauer et al., 2013): the likelihood method (Kemp-Benedict, 2008), the EBBN method (Wisse, van Gosliga, van Elst, & Barros, 2008) and the weighted sum algorithm. The likelihood method performed the best (lowest mean) while the EBBN performed worst (largest mean) for the conditional probability generation of the Car Diagnosis 2 model in Netica. Besides reducing the elicitation workload, the three methods also provide the alternative for probability specification when experts are unsure about some probability values.

The ranked node method developed by Fenton, Neil, and Caballero (2007) could generate full CPTs using some expressions. All nodes are defined on an underlying unit interval, [0-1]. For example, for a 5-point scale such as “very low”, “low”, “average”, “high”, and “very high”, the interval widths for each state are 0.2, where the term “very low” is associated with the interval [0-0.2) and the term “very high is defined to be [0.8-1.0]. To generate CPT, the experts only need to specify the relative weight for each parent node and choose one weight function, i.e. Mean Average, Minimum, Maximum and MixMinMax. With this method, if there are *k* parent nodes (*n* states each), the expert will only need to provide *k+1* parameter values. This method has been implemented in the commercial BN software, AgenaRisk, and was improved by Laitila (2013) both theoretically and computationally.

Meanwhile, it is advisable to assign the elicitation workload to different experts per their expertise. This will not only ease the elicitation burden on individual experts, but also improve the accuracy of the elicited probabilities.

Comparisons of the number of conditional probabilities to elicit using different techniques described above can be found in Table 3-1. The benchmark for comparison is N=$n_y \prod_{i=1}^{n} n_{X_i}$, which is the number of conditional probabilities to elicit for a node Y that has n_y states and n parent nodes, where each parent node I has n_{X_i} states.

3.2.3.2 Techniques for the elicitation of individual conditional probabilities

Individual probability could be elicited either directly or indirectly. Eight most widely used elicitation methods were summarized by (Kuhnert et al., 2010), i.e. elicitation of (1) probability, (2) frequency, (3) quantity, e.g. mean, (4) weighting, (5) quantitative interval, (6) probability distribution, (7) categorical measure, and (8) relative measure.

To help elicit quantitative probability numbers directly, methods such as the probability wheel, probability scale and gambling analogy can be used. Probability wheel is a pie chart which is divided into several partitions, each corresponding to one state of the studied node. Experts are asked to adjust the angular of the partitions until they are satisfied with the portions. Probability scale is a figure configured with numerical numbers as well as qualitative expressions, as illustrated in Figure 3-5 (van der Gaag, Renooij, Witteman, Aleman, & Taal, 1999) (Renooij, 2001).

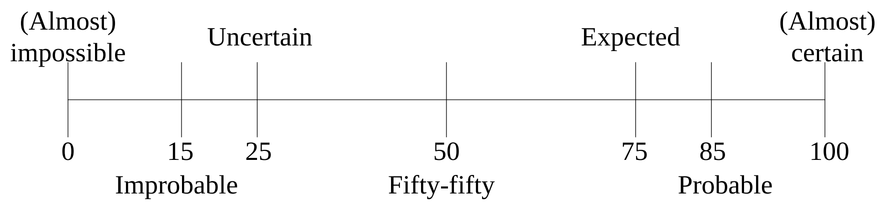


Figure 3-5 Probability scale
Source (Knochenhauer et al., 2013)

Table 3-1 Methods to reduce the number of conditional probabilities for elicitation

Method	Source	Node Type	Description	Conditional probabilities	Prerequisite for application
Node divorcing	(Knochenhauer et al., 2013)	Any	Reducing the number of parent nodes	Depends	Dependent on the causal logic/relations of the model
Noisy-OR	(Bolt & van der Gaag, 2010)	Binary nodes	Model individual probabilistic relations between each cause and effect individually	N=n	Satisfy independence and accountability
Noisy-Max	(Kraaijeveld, 2005)	Nominal nodes	Same as above. Extension of Noisy-OR	N= n_y $\sum_{i=1}^{n}(n_{X_i}-1)$	Same as above
Ranked node method	(Fenton et al., 2007); (Laitila, 2013)	Nominal nodes	The experts only need to specify the weight for each parent node and a proper algorithm	N=n+1	NA
Likelihood method	(Kemp-Benedict, 2008)	Any node type	The experts are asked about the influence weight instead of the direct conditional probability numbers	N=1+ $\sum_{i=1}^{n} n_{X_i} + 2n_y$	Proper to use when the parent nodes drive the child node away from its typical distribution. Guidelines only for nodes with 2 or 3 states.
EBBN	(Wisse et al., 2008)	Nominal nodes	It uses piecewise linear interpolation, based on the ranks of the parent nodes' states, to determine the CPT	N=n_y+2 $\sum_{i=1}^{n} n_{X_i} +2$	The values of child and its parent nodes could be ordered for either a positive or negative influence.
Weighted sum algorithm	(Hansson & Sjökvist, 2013)	Nominal nodes	The conditional probability is calculated as weighted sum of probability distributions over compatible parental configurations.	N=n+n_y $\sum_{i=1}^{n} n_{X_i}$	Need to find the compatible parental configurations

The gambling method defines probabilities either through the certain-equivalent method or the lottery-equivalent method. The former asks the expert to choose a direct reward *x* and a reward *r* that depends on the probability *p* until he/she is indifferent about the two rewards. The lottery-equivalent method, on the other hand, asks the expert to choose a lottery that depends on a given probability and *p* instead.

The fuzzy BN method proposed by J. Liu et al. (2003) and J Ren et al. (2005) (2009) integrated fuzzy set theory with BN, where linguistic variables were used for probability elicitation (J Ren et al., 2007). The integrated method is more practical for real world applications since the natural language is closer to the human cognition process.

Another widely used method is AHP, where experts can evaluate the probabilities by making paired comparisons about the relative likelihood of the possible states instead of directly providing the probability values. This way of elicitation is more logical (Bielza, Gomez, & Shenoy, 2010). However, the number of comparisons exceeds by far the number of conditional probabilities to elicit. To elicit n conditional probabilities, $n\times(n-1)/2$ comparisons need to be made with the AHP method.

The criteria for selecting the optimal elicitation techniques are feasibility and accuracy. Probability wheel is not suitable for the elicitation of very small or large probabilities. The gambling analogy and AHP are too time-consuming. Overall, the probability scale that maps qualitative statements to numerical values is preferred for its simplicity (Wiegmann, 2005).

3.2.3.3 Applications of the elicitation techniques for maritime safety modelling with BN

As discussed in Subsection 2.3.2, expert elicitation is the main source to obtain the parameters for maritime accidents modelling with BN. In most cases, both the structure and parameters of the network are to be obtained through experts' elicitation. For structure construction, models such as the Swiss cheese model and the Human Factors

Analysis and Classification System (HFACS) model have been used as a guiding framework. BNs models can also be converted from other models (e.g. FT). For probability elicitation, many techniques discussed in Subsection 2.3.3.2 have been used to aid the elicitation process. A more detailed review of the existing literature is provided below.

Det Norske Veritas (2003) (2006) obtained the prior and condition probabilities from both statistical data whenever possible, and from experts' elicitations when data are not available. A draft version of conditional probabilities was produced first, from which some typical and important ones were chosen for discussions in the elicitation workshop. Adjustments were made based on the discussions. Hänninen and Kujala (2012) carried out the sensitivity analysis with the DNV model to examine the model behaviour.

Partially based on the DNV model described above, Hänninen et al. (2012) developed an object-oriented BN (OOBN) to estimate the number of ship collisions in the Gulf of Finland in 2015. Parameters were adopted from the DNV model, with additional probability data defined based on local traffic data as well as using direct elicitation methods. Similarly, a BN model was built to assess the effect of Enhanced Navigation Support Information (ENSI) navigation service on both collision and grounding probabilities (Hänninen et al., 2013). Most variables and related conditional probabilities retained the values from (Det Norske Veritas, 2003) (Linn Kathrin Fjæreide, 2006). The CPTs for variables influenced by the new variable "ENSI" were assessed through experts' workshop using the probability scale.

Trucco et al. (2008) proposed the integration of the FTA and BN to model risks in the maritime transportation system. FT retraced the potential hazard until Basic Events (BE). BN was used to model the influences of common causes, mostly human and organizational factors and modify the probability of the BEs instead of generating the probability directly. Therefore, in the elicitation process, experts were asked to judge whether the probabilities of BEs will increase or decrease under the postulated set of organisational factors.

Jun Ren et al. (2008) utilized the "Swiss cheese" model to guide the construction of the BN model, for studying the collision risk between FPSO and authorized vessels. The Swiss cheese model provided guidance on the development of causal relationships, while BN enhanced the application of Swiss cheese model with quantitative algorithms. The fuzzy method using verbal expressions was applied to aid the conditional probability elicitation.

In (Y. F. Wang et al., 2010), the integration of HFACS, BN and Fuzzy Analytical Hierarchy Process (FAHP) were proposed for maritime accidents modelling, which was applied to a case study of the ship collision between Saetta and Conger in the Strait of Singapore. Similar to (Jun Ren et al., 2008), HFACS was used as guidance for the structure construction of the BN, while BN enabled the quantitative computations for the interplay between the causal factors. The indirect elicitation method FAHP was used for the definition of conditional probabilities. FAHP is the fuzzy version of AHP, where paired comparisions are made using fuzzy terms instead of crisp numbers like 1-9. To reduce the number of comparisons, a decomposition method was applied, which calculated the conditional probabilities for a multi-parent node by multiplying the conditional probabilities under individual parent nodes and a coefficient, as shown in the following function.

$$P\left(X = S_i \middle/ T^{(1)} = T_{p_j}^{(1)}, T^{(2)} = T_{p_j}^{(2)} \cdots T^{(n)} = T_{p_j}^{(n)}\right) = \alpha \prod_{j=1}^{n} \left(X = S_i \middle/ T^{(j)} = T_{p_j}^{(j)}\right) \tag{3-13}$$

Martins and Maturana (2013) proposed the integration of FTA, ETA and BN to model the human reliability related to the ship collision accident. Collision was modelled with FTA, the basic events of which were sequentially modelled using the ETA. BN was used to predict the probabilities for the basic elements in the ET, considering the influences of PSFs and MOFs. Most conditional probabilities were calculated using linear interpolation based on the number of positive states of the parent nodes. For example, for a node with 4 parent nodes, the conditional probability when *n* parent nodes took positive state was calculated as Min+(Max-Min)**n*/4, where Min and Max were the minimum and maximum conditional probability when all parent nodes took negative or positive states, respectively. The method is valid only if the maximum conditional probability occurs when all parent nodes take positive states and vice versa. The summary of the papers mentioned above can be found in Table 3-2.

Table 3-2 Elicitation techniques used in the BN models for maritime applications

Modelling event	Source	Elicitation burden reduction	Elicitation of individual probability
Collision for large passenger ship	(Det Norske Veritas, 2003)	-	Direct elicitation
ECDIS as risk reduction option for Grounding	(Linn Kathrin Fjæreide, 2006)	-	Direct elicitation
Number of Collisions	(Hänninen et al., 2012)	-	Direct elicitation
Collision for HSC	(Trucco et al., 2008)	-	Direct elicitation
Collision between FPSO and authorized vessels	(J Ren et al., 2007) (Jun Ren et al., 2008)	-	Fuzzy method, linguistic terms
ENSI effect on Collision and grounding	(Hänninen et al., 2013)	-	Probability scale
Collision	(Y. F. Wang et al., 2010)	Decomposition method	Fuzzy AHP, paired comparisons
Collision	(Martins & Maturana, 2013)	Linear interpolation depending on the number of parent nodes	-

3.3 Extension of BN with interval probabilitiess

3.3.1 Epistemic uncertainty and BN with interval probabilities

As discussed in Section 2.3.1, the epistemic uncertainty related with the expert's elicited BN is a huge challenge for BN applications, especially for the BN modelling of rare accidents such as ship collisions. J. Liu et al. (2003) reviewed three methods for uncertainty reasoning, i.e. the Bayesian theory, fuzzy set theory, and Dempster-Shafer (D-S) theory. The probability concept applied in BN can partly address the aleatory uncertainty by representing the events probabilistically instead of deterministically. The fuzzy set theory employs linguistic terms with corresponding membership functions as a way to represent vague information and address the epistemic uncertainty. D-S theory addresses epistemic uncertainty, using belief and plausibility. The integration of BN with fuzzy theory, i.e. fuzzy BN, has been applied to ship collision modelling (Jun Ren et al., 2008), which, to some extent, overcame the burden of crisp numbers required by BN. However, problems such as the construction of membership functions still exist.

On the other hand, interval theory is found to best represent the experts' knowledge due to more appropriate semantics (Fallet et al., 2011). It enables the representation of vague or incomplete information (Guo and Tanaka, 2010). The extension of BN with interval probabilities, with an upper and lower probability bound, is another way to address the epistemic uncertainty. Compared with the precise point probability numbers, the experts are always more comfortable in providing interval probabilities to represent the imprecision or vagueness in their judgement, especially when there is only little, incomplete or conflicting information available to assist their judgment (Guo & Tanaka, 2010). In other cases, when multiple experts are involved, each expert may provide their own belief without a group consensus (Cozman, 2000). Thus, interval probabilities are more appropriate to represent the ranges of all experts' judgement. Moreover, the interval probabilities are quite straightforward for users' understanding and interpretation.

Therefore, the extension of BN with interval probabilities is a good alternative to enhance the BN method and address the epistemic uncertainty when experts' opinions are employed in modelling.

3.3.2 Definition and properties of interval probability

An interval L=L_i=[L(a_i), U(a_i)], i=1,2,…,n is called the interval probability (Hu et al., 2012) if and only if for any P(a_i) that belongs to L_i , there are:

$$P(a_j) \in \left[L(a_j), U(a_j)\right], \qquad such \quad that \qquad P(a_i) + \sum_{j=1,2,\cdots i-1,i+1,\cdots n} P(a_j) = 1. \tag{3-14}$$

It has been proven that the a set of intervals will satisfy (3-14) if and only if, for any $i, j \in [1,\ldots,n]$, function (3-15) and (3-16) are satisfied (Tessem, 1992) (de Campos, Huete, & Moral, 1994) (Weichselberger, 2000):

$$\sum_{\substack{i=1 \\ i \neq j}}^{n} L(a_i) + U(a_j) \leq 1 \tag{3-15}$$

$$\sum_{\substack{i=1 \\ i \neq j}}^{n} U(a_i) + L(a_j) \geq 1 \tag{3-16}$$

In practice, it is not easy to check whether the elicited interval probabilities satisfy condition (3-15) and (3-16). However, it is easy to check whether they satisfy condition (3-17):

$$\sum_{i=1}^{n} L(a_i) \leq 1 \leq \sum_{i=1}^{n} U(a_i) \tag{3-17}$$

Condition (3-17) is a necessary but not sufficient condition of (3-14). For example, when n = 2, the interval L_1=[$L(a_1)$, $U(a_1)$] = [0.1,0.7], and interval L_2=[$L(a_2)$,$U(a_2)$]= [0.2,0.5], are not interval probability, even though they can satisfy (3-17). Because for $P(a_1)$=0.4 for example, there does not exist any probability $P(a_2)$ in L_2 so that $P(a_1)$+ $P(a_2)$=1. Probabilities that satisfy (3-17) are called semi-interval probabilities, denoted with [L'(a_i), U'(a_i)]. Linear programming was proposed by Guo and Tanaka (2010) to adjust [L'(a_i),U'(a_i)] to interval probabilities, as in function 3-18 below.

$$
\begin{aligned}
Max \quad & \sum_{i=1,2,\ldots n}^{n} \left(U(a_i) - L(a_i) \right) \\
s.t. \quad & \sum_{\substack{i=1 \\ i \neq j}}^{n} L(a_i) + U(a_j) \leq 1 \\
& \sum_{\substack{i=1 \\ i \neq j}}^{n} U(a_i) + L(a_j) \geq 1 \\
& U(a_i) \geq L(a_i) \\
& U(a_i) \leq U'(a_i) \\
& L(a_i) \geq L'(a_i) \\
& i = 1,2,\cdots n
\end{aligned}
\tag{3-18}
$$

The case of binary variables (n = 2) is simpler, since for j = 1 we can get the inequality according to (3-15) and (3-16):

$$L(a_2) + U(a_1) \leq 1 \tag{3-19}$$

$$U(a_2) + L(a_1) \geq 1 \tag{3-20}$$

Similarly, for j = 2, it is easy to obtain the inequalities:

$$L(a_1) + U(a_2) \leq 1 \tag{3-21}$$

$$U(a_1) + L(a_2) \geq 1 \tag{3-22}$$

From (3-19) and (3-22), L(a_2) + U(a_1) = 1 can be inferred; similarly, from (3-20) and (3-21), L(a_1) + U(a_2) = 1 can be obtained (Hall et al., 2005). Therefore, for binary variables, the probability boundaries for one state can be easily calculated from the boundary of another. For example, if L_1=[$L(a_1)$, $U(a_1)$] = [0.3,0.6], L_2 should be [$L(a_2)$, $U(a_2)$] = [1-0.6,1-0.3] = [0.4,0.7]. The interval probabilities calculated in this way not only save time but also ensure consistency.

3.3.3 Definition of credal network

BN with interval probabilities is a special type of credal network, which extends BN to deal with imprecision and uncertainty (Corani, Antonucci, & Zaffalon, 2012) (Avis & Fukuda, 1996). The following sections present the definition of BN with interval probability and describes its properties (Bolt & van der Gaag, 2010).

The general definition of credal network is as follows: a credal network over **X** is $\langle \zeta, \mathbb{P}_1, \ldots, \mathbb{P}_m \rangle$, where $\langle \zeta, \mathbb{P}_j \rangle$ is a BN over **X** for each $j = 1, \ldots, m$ (Antonucci and Zaffalon, 2008). A credal network can be regarded as a set of BNs, as explained through the example in Figure 3-6.

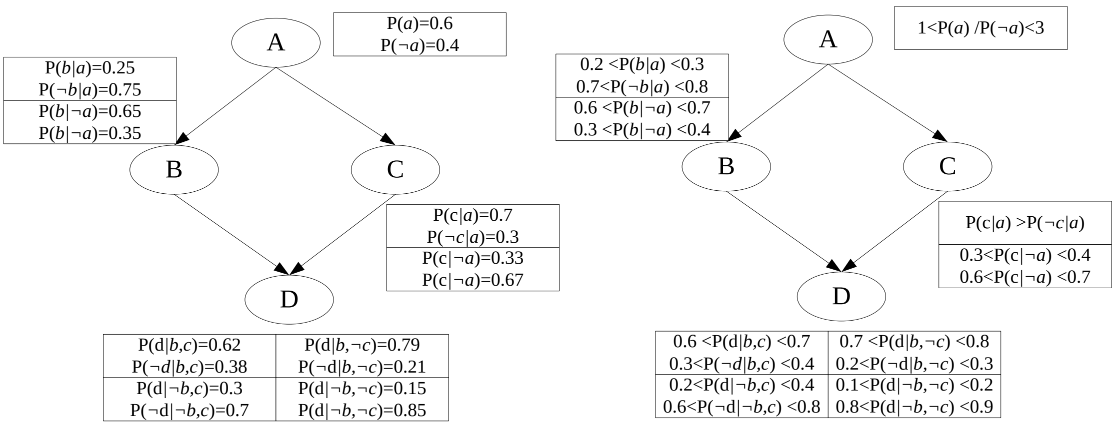


Figure 3-6 Comparison of BN and Credal network

Source (Author)

Figure 3-6a is an example of the traditional BN, where all probabilities are expressed with exact numbers. Figure 3-6b shows the credal network of the same structure. The probabilities in the credal network, however, are imprecise, enabling the representation of classificatory judgement, comparative judgement and conditional comparative judgement (Piatti et al., 2010). For example, the judgement 1<P(a)/P(¬a)<3 for node A, is a comparative judgement, indicating that the chance of '$A=a$' is one to three times higher than the chance '$A=\neg a$'. The probability of P(b|a) for node B, could be any value between

0.2 and 0.3. The BN in Figure 3-6a is just one among many others that satisfies the probability conditions of the credal network in Figure 3-6b.

It has been proven that the inferences over a credal network are equivalent to the inferences with the credal set for associated with the credal network (Antonucci, 2008). Meanwhile, inferences based on a credal set are equivalent to inferences with its vertices (Walley, 1991). However, the number of vertices is exponential to the input size, except for binary nodes who cannot have more than two vertices, making the inferences extremely hard compared to the traditional BN.

3.3.4 Updating algorithms for BN with interval probabilities

Even though the concept of extension from BN to credal network is quite simple, the probability updating for credal networks is much more complicated than the traditional BN. Hu, Luo, and Fu (2012) converted the interval probabilities into exact probability numbers for inferences. Ge, Zhou, Cui, and Yang (2013) decomposed the interval BN into two traditional point-valued BNs: one with the upper bound probabilities and another with the lower bound probabilities, which were then used as input for inferences in GeNie. Meanwhile, algorithms have been proposed for making inferences directly with interval probabilities in belief networks. Some of them are summarized below.

Support Logic Programming (SLP) and Interval Probability Theory (IPT) were used by Hall, Twyman, and Kay (2005) for inferences with interval probabilities, when studying the relationship between floods and climate changes. IPT introduced a parameter ρ to measure the dependence between propositions, which added extra workload in elicitation. Under the assumption of independency, IPT and SLP produced the same result. Meanwhile, with point probability input, SLP generated the same result as BN. W.-Y. Liu and Yue (2011) extended the Gibbs sampling algorithm to make updates with interval probabilities. The algorithm randomly assigns values for the non-evidence variables for initialization and repetitively updates the states based on the Markov blankets. This algorithm had been proved to converge. In addition to the above algorithms, a linear programming method was proposed by Antonucci, De Campos, Huber, and Zaffalon (2013) for approximate inferences.

The 2U algorithm proposed by Fagiuoli and Zaffalon (1998) is one of the most well known algorithm. The algorithm was extended from the Pearl's updating algorithm (Pearl, 2014) for the traditional BN by absorbing the constants. It is an exact inference algorithm for the binary polytree structured credal networks. The general formulas are as follows:

$$\underline{P}[x|e] = \left(1 + \left(\frac{1}{\underline{\pi}(x)} - 1\right)\frac{1}{\underline{\Lambda}^{X}}\right)^{-1} \tag{3-23}$$

$$\overline{P}[x|e] = \left(1 + \left(\frac{1}{\overline{\pi}(x)} - 1\right)\frac{1}{\overline{\Lambda}^{X}}\right)^{-1} \tag{3-24}$$

$$\underline{\pi}(x) = \min_{\substack{j \in \{1,\dots,n\} \\ \pi_X(u_j) \in \{\underline{\pi}_X(u_j), \overline{\pi}_X(u_j)\}}} \sum_U \underline{P}[x|U] \prod_i \pi_X(U_i) \tag{3-25}$$

$$\overline{\pi}(x) = \max_{\substack{j \in \{1,\dots,n\} \\ \pi_X(u_j) \in \{\underline{\pi}_X(u_j), \overline{\pi}_X(u_j)\}}} \sum_U \overline{P}[x|U] \prod_i \pi_X(U_i) \tag{3-26}$$

$$\underline{\Lambda}^{X} = \prod_j \underline{\Lambda}_{Y_j}^{X} \tag{3-27}$$

$$\overline{\Lambda}^{X} = \prod_j \overline{\Lambda}_{Y_j}^{X} \tag{3-28}$$

$$\underline{\pi}_{Y_j}(x) = \left(1 + \left(\frac{1}{\underline{\pi}(x)} - 1\right)\frac{1}{\prod_{k \neq j} \underline{\Lambda}_{Y_k}^{X}}\right)^{-1} \tag{3-29}$$

$$\overline{\pi}_{Y_j}(x) = \left(1 + \left(\frac{1}{\overline{\pi}(x)} - 1\right)\frac{1}{\prod_{k \neq j} \overline{\Lambda}_{Y_k}^{X}}\right)^{-1} \tag{3-30}$$

Equation (3-29) and (3-30) require the values of:

$$\underline{\Lambda}_X^{U_i} = \min_{\substack{j\in\{1,\ldots,n\},\, j\neq i \\ \pi_X(u_j)\in\{\underline{\pi}_X(u_j),\overline{\pi}_X(u_j)\}}} \left(\min_{\Lambda^X\in\{\underline{\Lambda}^X,\overline{\Lambda}^X\}} \hat{\underline{\Lambda}}_X^{U_i}\left(\Lambda^X\right) \right) \tag{3-31}$$

$$\overline{\Lambda}_X^{U_i} = \max_{\substack{j\in\{1,\ldots,n\},\, j\neq i \\ \pi_X(u_j)\in\{\underline{\pi}_X(u_j),\overline{\pi}_X(u_j)\}}} \left(\max_{\Lambda^X\in\{\underline{\Lambda}^X,\overline{\Lambda}^X\}} \hat{\overline{\Lambda}}_X^{U_i}\left(\Lambda^X\right) \right) \tag{3-32}$$

The values of $\hat{\underline{\Lambda}}_X^{U_i}\left(\Lambda^X\right)$ and $\hat{\overline{\Lambda}}_X^{U_i}\left(\Lambda^X\right)$ can be calculated according to Table 3-3 depending on value of Λ^X .

Table 3-3 Values of $\hat{\underline{\Lambda}}_X^{U_i}\left(\Lambda^X\right)$ and $\hat{\overline{\Lambda}}_X^{U_i}\left(\Lambda^X\right)$ depending on Λ^X

Condition	$\hat{\underline{\Lambda}}_X^{U_i}\left(\Lambda^X\right)$	$\hat{\overline{\Lambda}}_X^{U_i}\left(\Lambda^X\right)$
$\Lambda^X < 1$	$\dfrac{\hat{\overline{\rho}}(x\|u_i)+\left(\Lambda^X-1\right)^{-1}}{\hat{\underline{\rho}}(x\|\overline{u}_i)+\left(\Lambda^X-1\right)^{-1}}$	$\dfrac{\hat{\underline{\rho}}(x\|u_i)+\left(\Lambda^X-1\right)^{-1}}{\hat{\overline{\rho}}(x\|\overline{u}_i)+\left(\Lambda^X-1\right)^{-1}}$
$\Lambda^X = 1$	1	1
$\Lambda^X > 1$	$\dfrac{\hat{\underline{\rho}}(x\|u_i)+\left(\Lambda^X-1\right)^{-1}}{\hat{\overline{\rho}}(x\|\overline{u}_i)+\left(\Lambda^X-1\right)^{-1}}$	$\dfrac{\hat{\overline{\rho}}(x\|u_i)+\left(\Lambda^X-1\right)^{-1}}{\hat{\underline{\rho}}(x\|\overline{u}_i)+\left(\Lambda^X-1\right)^{-1}}$

Ide and Cozman (2004) extended the 2U method to Loopy 2U with a loopy step to deal with multi-connected networks. Even though 2U is an exact algorithm, L2U is only approximate. L2U performed better compared with two other apprimate inference methods, i.e. IPE (Iterated Partial Evaluation) and SV2U (structured variational methods), both in terms of time and accuracy. IPE could ensure convergence but is really slow and inaccurate. SV2U is comparativley accurate but is not capable of dealing with dense networks.

L2U was further developed to GL2U with an additional binarization step (Antonucci, 2008) (2010). The binarization step is to convert a generic credal networks into an equivalent binary credal network, which can then be solved by L2U. Under the binarization algorithm, a multistate node X_i with s_i states, can be equivalently represented by d_i=$\log_2|\Omega_{Xi}|$ binary nodes, where Ω_{Xi} is the smallest number over s_i that is an interger power of two. Each state of X_i can then be represented by the joint states of X_i^k (called bits of X_i), k=0, 1, …d_{i-1}. There will be an arc from the lower order to the higher order for bits of the same variables; for the bits of different variables, there will be an arc if and only if there was an arc between the orginal nodes. The approximation brought by the binarization algorithm can be removed by the Decision-Theoretic Specification (DTS) method by introducing a control node X_{i+n} for each X_i. All arcs previously pointing to X_i will be redirected to X_{i+n}, and there will be new arcs from X_{i+n} to X_i. The sequential use of the DTS and binarization algorithm produces an exact equivalent binary credal network. Therefore, the only approximation remaining in GL2U is related to the loopy step. In this study, the GL2U algorithm was used for the probability updates.

CHAPTER 4 Application of BN with Interval Probabilities for Ship Collision Causation Probability Modelling

4.1 Construction of the BN stucture to model the causation probability of collisions

4.1.1 Accident causal models

Accidents always have long incubation periods with a lot of warning signals such as incidents, near misses, and minor accidents (Skogdalen & Vinnem, 2012). (M. R. Grech, Horberry, & Smith, 2002) pointed out that there are 100 plus incidents and 10 to 100 near misses for every accident. The development process of accidents involves three stages: initiating, contributing, and propagating (Bea, 2011). Maritime incidents are abnormal events (less serious than accidents) occurring during the operation of sea-going ships that are likely to cause danger or damage to man, ships, and the environment (Kuehmayer, 2008). Examples of maritime incidents include loss of control of ships due to engine, propeller and rudder failure, extraordinary listing, fuel/fresh water shortage, navigation /safety obstruction and so on. In the maritime domain, the causal chain (Figure 4-1) provides a tool for understanding the causes and developments of maritime accidents.

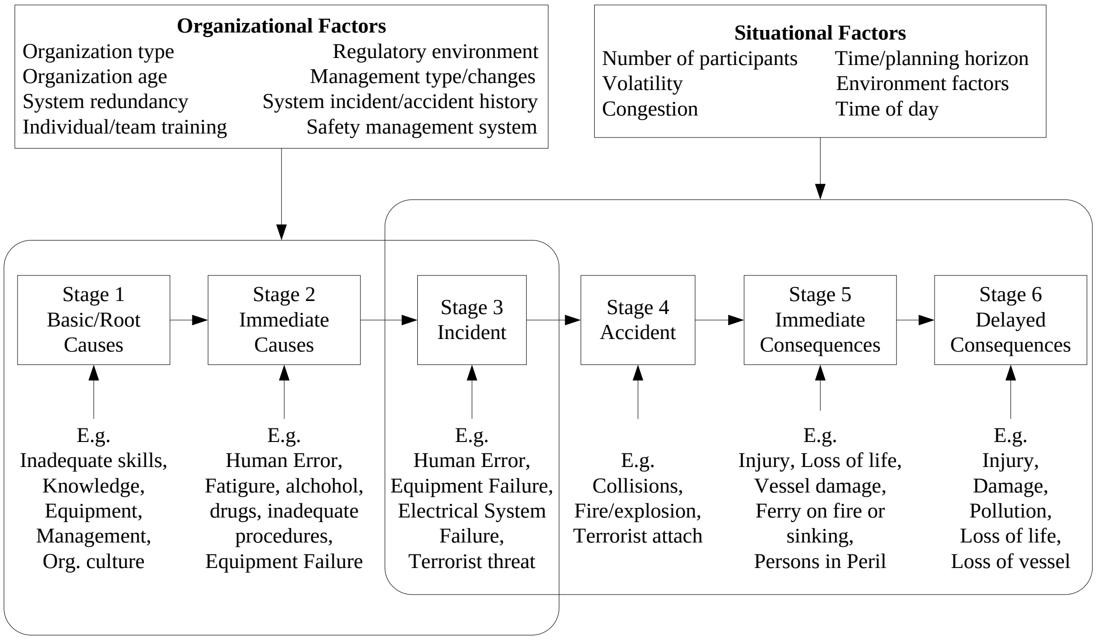


Figure 4-1 Accident causal chain

Source (Grabowski, Merrick, Harrold, Massuchi, & van Dorp, 2000)

Due to the technical improvements, human errors have become the main contributor as the immediate cause for maritime accidents nowadays (Trucco et al., 2008) (O'Neil, 2003). Statistics showed that 75-96% of marine accidents (89-96% of collisions, 79% of towing vessel groundings, 84-88% of tanker accidents) could be attributed to human errors (Jun Ren et al., 2008). Similar findings were discovered by Baker and Seah (2004), where human error accounted for 84%, 85% and 82% of the maritime accidents recorded in ATSB, TSB and MAIB respectively. Meanwhile, various human factors (e.g. fatigue, situation awareness) and organizational factors (e.g. organizational structures, procedures, report line and organizational culture) are the underlying causes. In the maritime domain, there was a shift of focus, first from technical aspects to individual human factor and then to a system perspective (M. Grech, Horberry, & Koester, 2008) with more consideration of the organizational factors. Human and organizational factors must be considered for maritime accident modelling to get reliable results.

The SHEL (software, hardware, environment, liveware) model, Swiss Cheese model, and HFACS model are the three most well-known frameworks for analysing human and organizational factors. HFACS, for example, defines four tiers of causal factors: unsafe acts, preconditions to unsafe acts, unsafe supervision, and organizational influences (D. Liu, Nickens, Hardy, & Boquet, 2013) (Shappel & Wiegmann, 2000) (Celik & Er, 2007). The hierarchical framework is always used as a classification tool to extract causal relationship from accident narratives (S.-T. Chen & Chou, 2012) (S.-T. Chen et al., 2013). Nevertheless, they lack the quantitative capabilities. In applications, they could be used as guidelines for the development of causal relationships for BN structure construction while BN could enhance their application with quantitative algorithm for the maritime accidents modelling (Jun Ren et al., 2008) (Y. F. Wang et al., 2010) (Akhtar & Utne, 2014).

4.1.2 Causal factors for ship collision accidents

Knowledge of the maritime system is important for establishing the causation probability model (Friis-Hansen, 2008). Collision investigation reports from Marine Accident Investigation Authorities, such as MAIB, TSB and ATSB, provide good channels of resources, where detailed narratives and analyses for historical collisions are easily accessible. The major common causal factors for historical collisions are summarized in the following paragraphs. However, it should be noted that tragedies are never caused by a single factor but are associated with the interactions of multiple factors in the complex socio-technical system.

The accident causes can be crudely separated into human errors and equipment failure, resulting from either ship board operations or shore management (Ladan & Hänninen, 2012). Friis-Hansen (2008) classified causes of ship collisions into four main groups: 1. failure in manoeuvring, 2. incapacitation of personnel, 3. technical problems and 4. environmental causes. Similarly, Mazaheri (2009) adopted five categories: 1. human factors, 2. vessel specifications, 3. route characteristics, 4. atmospheric factors or weather conditions, 5. situational factors. Based on this, the following factors which impinge on collision probabilities are summarized.

Human factors

- Lack of knowledge/Skills. Qualification of the crew is crucial to the safety performance of ships. Many collisions happened because of the OOW's unsound judgments and wrong actions against COLREG, due to inadequate/incorrect knowledge or lack of skills to deal with emergency manoeuvring tasks under critical situations. Meanwhile, the inability to unload lifeboat could incredibly reduce the chance of surviving for the people on board after collisions.

- Fatigue. Fatigue may cause delays in response and difficulties in memory or retention, which in turn lead to accidents. Factors such as prolonged working hours, disorders of sleep, change of shift and circadian rhythm as well as the harsh environment on board ships, all increase the likelihood of fatigue. Some ships have installed devices like the watch alarm to prevent the OOW from falling asleep. Unfortunately, they were found to have been switched off deliberately in many collision investigations.

- Distraction. Multitasking is quite common on board. On top of the navigation tasks, the OOW are often occupied by administration jobs as well. Other forms of distractions also exist, such as chatting on the bridge or over the phone etc. Some shipping companies have adopted the "Red bridge" system which rigorously controls access to the bridge during busy waterways to reduce the distractions.

- Complacent. Many collisions happened when the higher rank crew (masters) dismissed the lookout person, which indirectly led to the occurrence of collisions. The complacent altitude of some experienced officers has also caused collisions for trusting their own judgement without verifying them with the navigational system.

- Solo watch. Solo watch is a very hazardous scenario for navigation, especially in the night time, under reduced visibility or for high traffic waterway.

- Consumption of Alcohol. Although alcohol is generally prohibited onboard, it was found have caused several previous collisions.

- Blindly following the navigational devices. Even though automation has improved the accuracy of navigation, exclusive reliance on technology can decrease situational awareness. The navigational devices work well only for specific ranges. Moreover, signals of small ships such as fishing vessels and recreational yachts, are often difficult to acquire and unstable to maintain on the navigational system as well, especially in rough weather and high waves. Therefore, it is dangerous to blindly follow the navigational devices.

- Other personal factors including excessive stress, physical unfitness, carelessness, ignorance and laziness.

Organisational factors

- Production orientation. The pressure of avoiding delays and meeting schedules may drive the sacrifice of safety performance.

- Power distance. The hierarchical power pyramid on ships constitutes a barrier for the junior officers or non-officers to challenge the decisions made by a high rank officer. The situation is more complicated when a third party pilot is involved. Had the third officer taken the con from the PEC holder, the collision between Stena Feronia and Union Moon (MAIB, 2012) could have been avoided.

- Safety culture. Both the human and technical performances are influenced by the company's safety culture, such as how safety issues are addressed and how the safety mindset is promoted (Linn Kathrin Fjæreide, 2006).

- Procedure. Incomplete procedures or noncompliance with the procedures can cause detrimental consequences. For example, the lack of standard procedures about when to call for master can lead to a waste of precious time for effective collision avoidance.

- Communication. Communication is always challenging on ships which carry the most diverse nationals. The language problems as well as culture difference hinder smooth communications among the crew, between the crew and third party personnel (pilots), as well as between ships. One direct outcome of miscommunication is the serious deviation of manoeuvres from the original intents, which may in turn develop into devastating situations.

- Bridge Resource Management (BRM). The proper use of all available resources is of great significance for collision prevention in the early phase and for collision avoidance under critical operations.

- Crew size. Reduced manning level increases the workload and leads to fatigue.

- Training. The shipping company should identify the areas for training, and provide the necessary resources to address the needs of their crew.

- Other management factors include voyage planning, maintenance, shift change etc.

Technical factors

- Ship particulars such as ship type, size, speed and loading conditions contribute to collisions by affecting the manoeuvrability of ships. Detectability also differs for different size of vessels.

- Bridge layout. The ergonomics of bridge layout may affect the performance of the Officer on Watch (OOW). For example, the blind corners by the crane have caused collisions by blocking the view of the OOW.

- Advanced navigational aids. The use of modern navigation equipment, such as Automatic Radar Plotting Aid (ARPA), Electronic Chart Display and Information System (ECDIS) etc., can improve navigation safety considerably.

- Vessel Traffic Service (VTS). The presence of VTS can create external vigilance and reduce the causation probability for collisions.

- VHF. Even though VHF provides a channel for communication, it should never be used for collision avoidance.

- Technical failures in propulsion or steering system, radar, Global Positioning System (GPS) etc.

- Other factors including TSS, Pilot's assistance, Tug assistance, etc.

Environmental factors

- Traffic intensity and composition. Extra attention should be paid for navigation in busy waterways, especially when a lot of fishing vessels are around, since their movements are unpredictable.

- Navigational complexity related with geographical conditions as well as the traffic density of the area poses a great challenge for shipping safety.

- Weather condition. Most accidents happened in bad weather conditions, such as raining and reduced visibility.

- Time (day, night). This factor mainly influences visibility.

- Visibility (fog, precipitation). Visibility affects both visual detection and navigational system detection of nearby vessels. It is conditional on weather and time of the day.

- Other factors such as wave, wind; current; tide; ice etc.

4.1.3 Ship collision causation probability-A state of the art model

Based on the causal factors identified above, as well as reference to the collision investigation reports and the previous models in the literature, especially the models in (Friis-Hansen & Simonsen, 2002) and (Det Norske Veritas, 2003), a state of the art BN model was built in the present study.

There were three critical nodes, "Detection" "Manoeuvre planning" and "Manoeuvring", corresponding to the three main cognitive functions for successful collision avoidance under critical situations, similar to the studies of Montewka and Goerlandt (2013) and

Leva, Friis-Hansen, Ravn, and Lepsoe (2006). Successful "Detection" could be achieved through "Navigation system detection", "Visual detection" or "VTS detection". Meanwhile, successful "Detection" was the prerequisite for correct "Manoeuvre planning", which was in turn the prerequisite for correct "Manoeuvring". Collision was modelled as the result of manoeuvring actions of both encountering ships. The logic is reflected in the CPT, as in Table 4-1 and Table 4-2.

Table 4-1 Conditional probabilities for the node "Detection"

Navigation system detection	Yes				No			
Visual detection	Yes		No		Yes		No	
VTS detection	Yes	No	Yes	No	Yes	No	Yes	No
Detection=Yes	1	1	1	1	1	1	1	0
Detection=No	0	0	0	0	0	0	0	1

Table 4-2 Conditional probabilities for the node "Manoeuvre planning"

Detection	No							
Navigational complexity	High				Low			
Competence of the OOW	High		Low		High		Low	
Communication between ships	Yes	No	Yes	No	Yes	No	Yes	No
Correct Manoeuvre planning	0	0	0	0	0	0	0	0
Incorrect Manoeuvre planning	1	1	1	1	1	1	1	1

The causal factors such as vessel specifications, route characteristics, weather conditions human and organizational factors (Mazaheri, 2009) were included by exerting influences to the three critical cognitive functions. The total number of nodes was controlled to as few as possible so that the elicitation workload could be manageable. The detailed model is presented in Figure 4-2. There are two sets of variables with the same definition and same causal structure, corresponding to each ship in Figure 4-2. The eight nodes in the middle i.e. "Time of day", "Visibility", "Weather", "VTS Presence", "VTS Detection", “Navigational complexity” “Communication between ships” and “Collision” are the common influencing factors for both ships.

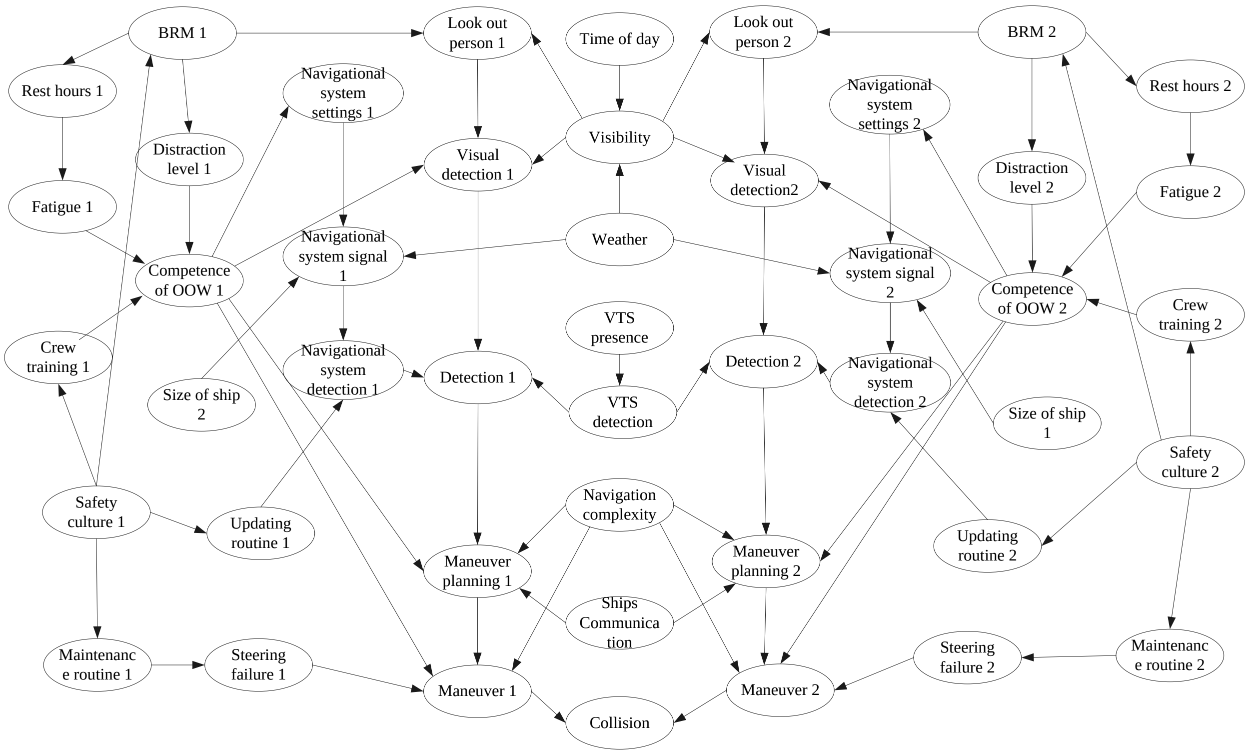


Figure 4-2 BN model for the causation probability prediction of ship collisions

Source (author)

The states and a brief description for the nodes could be found in Table 4-3.

Table 4-3 Nodes and states of the BN model for causation probability prediction in this study

Node	States	Brief descriptions
Collision	Yes; No.	Whether collision happens or not
Manoeuvring 1 (2)	Correct; Incorrect.	Whether manoeuvring the desired avoidance action according to COLREG.
Manoeuvre planning 1 (2)	Correct; Incorrect.	Emergency passing plan after detection.
Updating routine 1 (2)	Followed; Not followed.	Whether the OOW frequently checks and updates the navigational equipment.
Navigational system signal 1 (2)	Good; Bad.	Whether there are strong/stable signals on the navigation system, depending on the system settings, size of the other ship and the weather.
Navigational system	Correct;	Whether the navigational system such as the Radar and

Table 4-3 Nodes and states of the BN model for causation probability prediction in this study (continued)

Node	States	Brief descriptions
settings 1 (2)	Incorrect.	AIS are set to the right range and tuned properly.
Navigational system detection1 (2)	Yes; No.	Whether another ship is detected through the navigation system.
Look out person 1 (2)	Yes; No.	Whether an additional look out person is assigned.
Visual detection 1 (2)	Yes; No.	Whether another ship is detected visually.
VTS Presence	Yes; No.	Whether VTS service is available for the area.
VTS Detection	Yes; No.	Meaning whether a potential collision situation is detected by VTS and communicated to the OOW.
Detection 1 (2)	Yes; No.	Detection of another ship through navigational system, VTS or visually.
Rest hours 1 (2)	Adequate; Less than adequate.	Whether the OOW got enough rest.
Fatigue 1 (2)	Yes; No.	Whether the OOW is fatigued.
Distraction level 1 (2)	High; Low.	Level of distraction of the OOW by administrative tasks, talking with people on board or over the phone, etc.
Crew training 1 (2)	Adequate; Less than adequate.	Whether the OOW has got enough training.
Competence of the OOW 1 (2)	High; Low.	This can be improved by training and reduced by fatigue and distractions.
Safety culture 1 (2)	Good; Bad.	Safety culture is the core for safety performance.
Maintenance routine 1 (2)	Followed; Not followed.	Whether the crew follows the maintenance routine to minimize the breakdown of machinery.
BRM1 (2)	Good; Bad.	Good BRM makes good use of the available resources.
Weather	Good; Bad.	Bad weather has contributed to many previous accidents.
Visibility	Adequate; Less than adequate.	
Size of encounter ship 1 (2)	Big; Small.	The ship size influences thse signal quality they generate on radar.
Communication	Yes; No.	Communication between the encounter ships.
Steering failure 1 (2)	Yes; No.	Whether there is a steering failure.
Navigational complexity	High; Low.	Complexity for navigation, depending on the geographical situation and traffic intensity.
Time of the day	Daytime; Night.	

4.2 Parameters for the BN model

4.2.1 Data collection process

4.2.1.1 Expert Elicitation tool

In this study, due to the lack of data, the parameters of the BN model for the collision causation probability analysis was mainly specified by domain experts. Interval probabilities rather than point probabilities are elicited to represent the ambiguity in the elicited knowledge. Two versions of elicitation tool were developed. Figure 4-3 illustrates the first elicitation tool developed as a Java package.

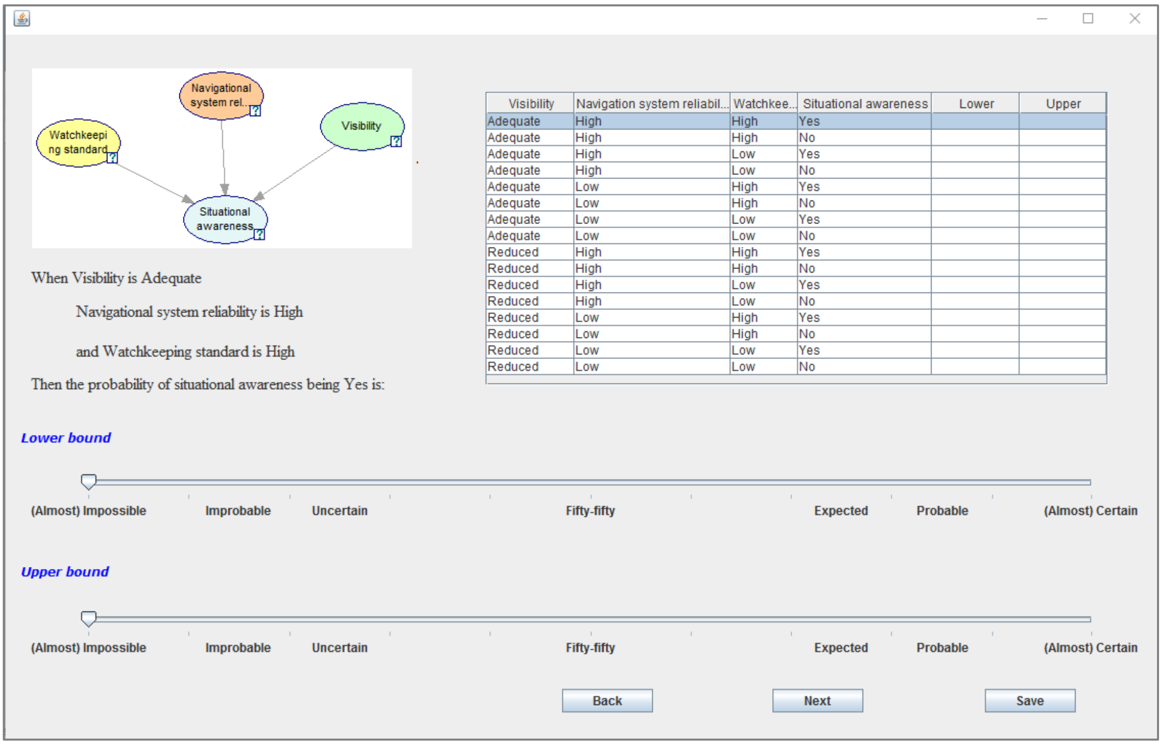


Figure 4-3 First version of elicitation tool for the collision causation probability model

Source (author)

The expert can define the upper and lower bound for each interval conditional probability by simply dragging the corresponding sliders. Verbal description is also provided on each slider. The numbers in the conditional probability table on the right corner change simultaneously with the movement of the slider. The “back” button provides a path of return to the main page, from where the user can switch to different nodes for elicitation. The “next” button directs to the next item for elicitation within the conditional probability table. By clicking the “save” button, the elicited probabilities can be exported into an excel file for future use.

However, during the test phase, this first version tool was found to be confusing. Instead of making the elicitation easier, the use of the two sliders added complexity to the cognitive process. The experts got lost about the meaning of the probability numbers during the long elicitation process with hundreds of numbers to elicit. Therefore, even though the sliders gave flexibility in specifying the interval conditional probabilities, they were discarded for the lack of brevity for practical applications.

A closer examination revealed that linguistic terms such as “Likely”, “Very likely”, “Unlikely”, “Very unlikely”, were more friendly to use, since these natural language terms corresponded to human cognition. They can also represent imprecise or vague information. The application of linguistic terms defined with interval probabilities could be found in many previous studies (Antonucci, Huber, et al., 2013; Mastrandrea et al., 2010; J Ren et al., 2007). Therefore, the second version elicitation tool incorporated the linguistic terms for its simplicity and straightforwardness.

The definitions of linguistic terms from six sources with associated intervals are compared in Figure 4-4 (WMO, 2005) (J Ren et al., 2009) (Antonucci, Huber, et al., 2013) (Berkman Solutions, 2014) (Plato, 2013) (Beasley). The detailed definition of the intervals linked with linguistic terms from these six sources can be found in Table 4-4.

The linguistic terms from source 1 were adopted in the second version elicitation tool, which was an excel-based questionnaire, as shown in Figure 4-5. Instead of required to provide two bounds for each conditional probability, the expert can specify the interval probability by choosing the proper linguistic terms from a dropdown list, which is comparatively easy and more suitable for fast elicitation of a large number of probabilities.

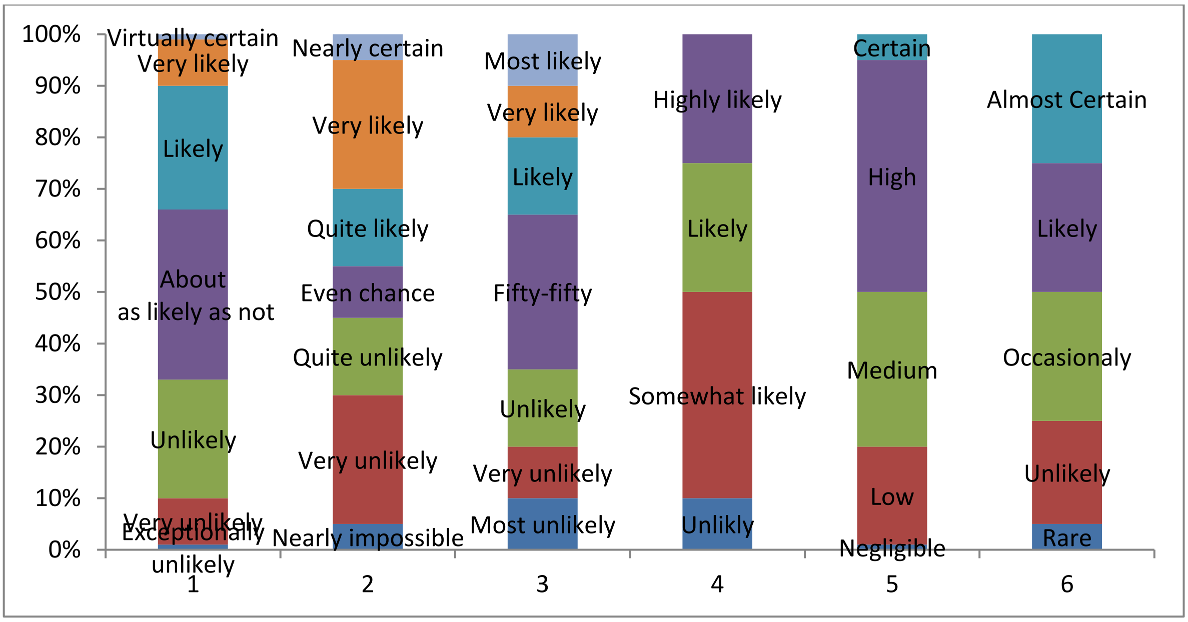


Figure 4-4 Comparison of scaling of the linguistic terms with probability intervals

Source (author)

Table 4-4 Scaling of the linguistic terms with probability intervals

(1) (WMO, 2005)		(2) (J Ren et al., 2009)		(3) (Antonucci, Huber, et al., 2013)	
Virtually certain	(99%,100%]	Nearly certain	(95%,100%]	Most likely	[90%,100%]
Very likely	(90%,99%]	Very likely	(70%,95%]	Very likely	[80%,90%]
Likely	(66%,90%]	Quite likely	(55%,70%]	Likely	[65%,80%]
About as likely as not	[33%,66%]	Even chance	(45%,55%]	Fifty-fifty	[35%,65%]
Unlikely	[10%,33%)	Quite unlikely	(30%,45%]	Unlikely	[20%,35%]
Very unlikely	[1%,10%)	Very unlikely	(5%,30%]	Very unlikely	[10%,20%]
Exceptionally unlikely	[0%,1%)	Nearly impossible	[0%,5%]	Most unlikely	[0%,10%]
(4) (Berkman Solutions, 2014)		(5) (Plato, 2013)		(6) (Beasley)	
Highly likely	[75%,100%]	Certain	[95%,100%]	Almost Certain	[75%,100%]
Likely	[50%,75%)	High	[50%,95%)	Likely	[50%,75%)
Somewhat likely	[10%,50%)	Medium	[20%,50%)	Occasionally	[25%,50%)
Unlikely	[0%,10%)	Low	[1%,20%)	Unlikely	[5%,25%)
		Negligible	[0%,1%)	Rare	[0%,5%)

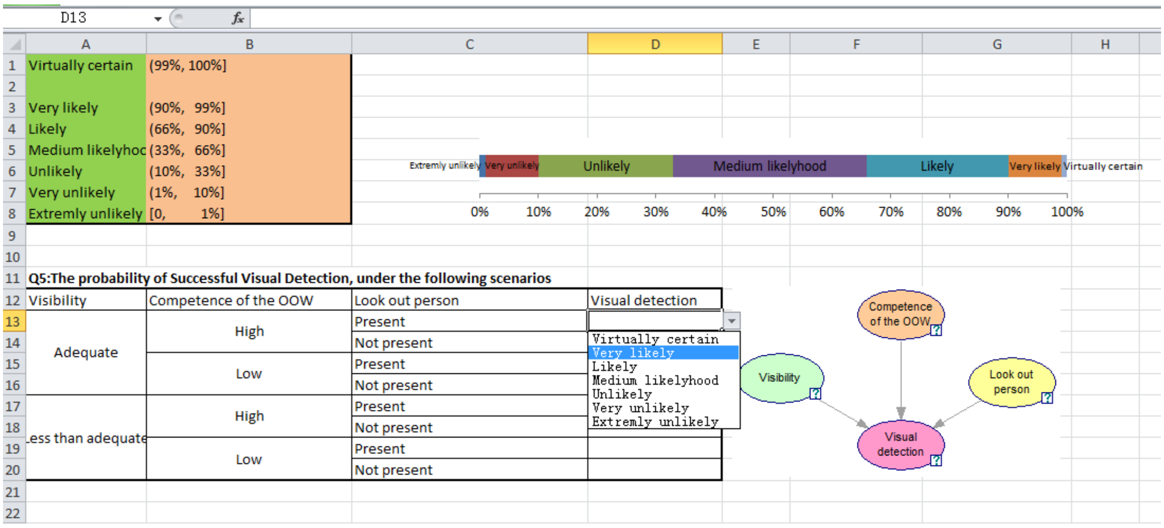


Figure 4-5 Second version elicitation tool for the collision causation probability model

Source (author)

There is a trade-off between convenience and flexibility, since the elicited probabilities will be fixed for choice of the same term. More discussions on this trade-off can be found in the results discussion section.

4.2.1.2 Combination of the experts' opinion

The probability elicitation process typically involves more than one expert. In such cases, the elicitation can be conducted either collectively or individually, meaning either to obtain the CPTs from group workshops with the consensus from all experts, or to conduct individual session and derive one set of CPTs from each expert. The latter option was adopted in this study. To combine the conditional probabilities provided by different experts, a weighted average method was used, as described below.

One weight number was attached to each judgement made by the experts, rather than to each expert. Therefore, the weight for the same expert might vary for the different judgements they made for different nodes. More weight was assigned to the judgments that were closer to the judgments provided by all other experts, and vice versa. More specifically, the weight W^b for the interval L^b was in reciprocal ratio to the distance D^b between this interval and all other intervals under the same instantiation.

The distance D^b between interval L^b=[$L^b(a_i)$, $U^b(a_i)$] and all other intervals [$L^j(a_i)$, $U^j(a_i)$], where $j = 1,2\ldots b\text{-}1, b+1,\ldots m$ (m was the total number of experts) was calculated through function (4-1) (Hu et al., 2012):

$$D^b = \frac{1}{m-1}\sum_{\substack{j=1 \\ j\neq b}}^{m}\sqrt{\left(L^j(a_i) - L^b(a_i)\right)^2 + \left(U^j(a_i) - U^b(a_i)\right)^2} \tag{4-1}$$

As such, the weight W^b for [$L^b(a_i)$, $U^b(a_i)$] was defined as k/D^b, where k was a constant number. Since all weights should add up to 1, equation (4-2) could be obtained:

$$\frac{k}{D^1} + \frac{k}{D^2} + \cdots \frac{k}{D^{b-1}} + \frac{k}{D^b} + \frac{k}{D^{b+1}} + \cdots \frac{k}{D^m} = 1 \tag{4-2}$$

Therefore, the value of k could be obtained, as well as the weight W^b, without additional evaluation by the experts. The interval probabilities combined in this manner were closer to the judgement provided by the majority of the experts.

4.2.2 The conditional probabilities originally elicited from the experts

The excel based elicitation tool described in Figure 4-5 was used in the actual probability elicitation process from the navigational experts. Several techniques were employed to alleviate the elicitation workloads, i.e. reducing the number of conditional probabilities to elicit. First, since the collision model had two sets of same nodes with the same causal structure (see Section 4.1.3), elicitation was only conducted for one set, which were applied to the other set. Second, elicitation was conducted only for one state for each node. The interval probability for the other state was obtained according to equations $L(a_2) + U(a_1) = 1$ and $L(a_1) + U(a_2) =1$, where $L(a_1)$ ($L(a_2)$) is the lower probability bound for state 1 (2), and $U(a_1)$ ($U(a_2)$) is the upper probability bound for state 1(2). The interval probabilities calculated using this rule can ensure consistency without further adjustments.

Third, the probability table for the node “Detection” was defined based on the logic rule rather than relying on the elicitation, as seen in Table 4-1.

The elicitation was conducted through individual face to face interviews with navigational experts in Singapore who are ship masters, managers and officers with many years of sailing experiences. Before elicitation, the experts were briefed about the research objectives as well as the elicitation tool. The duration of the elicitation process per expert varied from one to two hours. In total, eleven completed questionnaires were collected from individual interviews with twelve navigational experts. Three of the experts were very experienced ex-captains with more than twenty years sailing experience. One was an expert in ship management with more than ten years’ experience in safety management of ships in addition to a few years’ sailing experience. One superintendent with more than five years sailing experience also participated. The remaining seven participants were younger officers with two to five years sailing experiences.

The original elicited results were in the form of natural language. Table 4-5 shows the originally elicited CPT for the node “Visual detection”. The linguistic terms were converted into the corresponding interval probabilities based on Table 4-4. Table 4-6 presents the converted interval CPT from Table 4-5. The elicited CPTs for all nodes from the 11 questionnaires were collated and attached in Appendix A.

Table 4-5 The originally elicited CPT for the node “Visual Detection”

Visibility	Competence of the OOW	Look out person	Visual Detection=Yes 1	2	3	4	5	6	7	8	9	10	11
Adequate	High	Present	Virtually certain	Very likely	Very likely	Very likely	Very likely	Very likely	Virtually certain	Likely	Virtually certain	Very likely	Very likely
		Not present	Very likely	Likely	Very likely	Likely	Very likely	Likely	Unlikely	Very likely	Virtually certain	Likely	Likely
	Low	Present	Very likely	Likely	Very likely	Very likely	Very likely	Likely	Likely	Likely	Virtually certain	Likely	Likely
		Not present	Unlikely	Medium likelihood	Likely	Medium likelihood	Medium likelihood	Medium likelihood	Extremely unlikely	Medium likelihood	Very likely	Medium likelihood	Unlikely
Less than adequate	High	Present	Very likely	Likely	Medium likelihood	Very likely	Medium likelihood	Very likely	Very likely	Medium likelihood	Very likely	Likely	Likely
		Not present	Very unlikely	Likely	Medium likelihood	Medium likelihood	Medium likelihood	Likely	Extremely unlikely	Medium likelihood	Very likely	Medium likelihood	Unlikely
	Low	Present	Likely	Unlikely	Medium likelihood	Likely	Unlikely	Medium likelihood	Unlikely	Medium likelihood	Very likely	Medium likelihood	Unlikely
		Not present	Extremely unlikely	Very unlikely	Unlikely	Unlikely	Unlikely	Unlikely	Extremely unlikely	Very unlikely	Likely	Unlikely	Very unlikely

Table 4-6 The converted CPT for the node “Visual Detection”

Visibility	Competence of the OOW	Look out person	Visual Detection=Yes											Combined probability	
			1	2	3	4	5	6	7	8	9	10	11	Lower bound	Upper bound
Adequate	High	Present	0.99-1	0.9-0.99	0.9-0.99	0.9-0.99	0.9-0.99	0.9-0.99	0.99-1	0.66-0.9	0.99-1	0.9-0.99	0.9-0.99	0.912	0.990
		Not present	0.9-0.99	0.66-0.9	0.9-0.99	0.66-0.9	0.9-0.99	0.66-0.9	0.1-0.33	0.9-0.99	0.99-1	0.66-0.9	0.66-0.9	0.761	0.927
	Low	Present	0.9-0.99	0.66-0.9	0.9-0.99	0.9-0.99	0.9-0.99	0.66-0.9	0.66-0.9	0.66-0.9	0.99-1	0.66-0.9	0.66-0.9	0.760	0.936
		Not present	0.1-0.33	0.33-0.66	0.66-0.9	0.33-0.66	0.33-0.66	0.33-0.66	0-0.01	0.33-0.66	0.9-0.99	0.33-0.66	0.1-0.33	0.327	0.615
Less than adequate	High	Present	0.9-0.99	0.66-0.9	0.33-0.66	0.9-0.99	0.33-0.66	0.9-0.99	0.9-0.99	0.33-0.66	0.9-0.99	0.66-0.9	0.66-0.9	0.719	0.901
		Not present	0.01-0.1	0.66-0.9	0.33-0.66	0.33-0.66	0.33-0.66	0.66-0.9	0-0.01	0.33-0.66	0.9-0.99	0.33-0.66	0.1-0.33	0.357	0.623
	Low	Present	0.66-0.9	0.1-0.33	0.33-0.66	0.66-0.9	0.1-0.33	0.33-0.66	0.1-0.33	0.33-0.66	0.9-0.99	0.33-0.66	0.1-0.33	0.327	0.598
		Not present	0-0.01	0.01-0.1	0.1-0.33	0.1-0.33	0.1-0.33	0.1-0.33	0-0.01	0.01-0.1	0.66-0.9	0.1-0.33	0.01-0.1	0.073	0.229

Table 4-7 Illustration of the probability combination process for the last row of Table 4-6

Expert NO.	Intervals	Lower bounds	Upper bounds	Distance (D)	Weight (k/D)
1	0-0.01	0	0.01	0.306	0.077
2	0.01-0.1	0.01	0.1	0.245	0.096
3	0.1-0.33	0.1	0.33	0.221	0.106
4	0.1-0.33	0.1	0.33	0.221	0.106
5	0.1-0.33	0.1	0.33	0.221	0.106
6	0.1-0.33	0.1	0.33	0.221	0.106
7	0-0.01	0	0.01	0.306	0.077
8	0.01-0.1	0.01	0.1	0.245	0.096
9	0.66-0.9	0.66	0.9	0.930	0.025
10	0.1-0.33	0.1	0.33	0.221	0.106
11	0.01-0.1	0.01	0.1	0.245	0.096
Average		0.073	0.229	k=0.0235	

4.2.3 Combination of the conditional probabilities elicited from the experts

The probability numbers provided by all the 11 experts were combined with the weighted average method described in Section 4.2.1.2. The last two columns of Table 4-6 show the combined conditional probability interval bounds for the node "Visual detection". For illustration purpose, the combination process for the last row of Table 4-6 is explained below.

First, the distance between one interval and all other intervals was computed. For example, the distance for the interval provided by expert one (D^1) could be calculated as follows:

$$\begin{aligned}
D^1 &= \frac{1}{m-1}\sum_{j=2}^{m}\sqrt{\left(L^j(a_i)-L^1(a_i)\right)^2+\left(U^j(a_i)-U^1(a_i)\right)^2} \\
&= \frac{1}{10}\left(\begin{array}{l}
\sqrt{(0.01-0)^2+(0.1-0.01)^2}+\sqrt{(0.1-0)^2+(0.33-0.01)^2}+\sqrt{(0.1-0)^2+(0.33-0.01)^2} \\
+\sqrt{(0.1-0)^2+(0.33-0.01)^2}+\sqrt{(0.1-0)^2+(0.33-0.01)^2}+\sqrt{(0-0)^2+(0.01-0.01)^2} \\
+\sqrt{(0.01-0)^2+(0.1-0.01)^2}+\sqrt{(0.66-0)^2+(0.9-0.01)^2}+\sqrt{(0.1-0)^2+(0.33-0.01)^2} \\
+\sqrt{(0.01-0)^2+(0.1-0.01)^2}
\end{array}\right) \\
&= 0.306
\end{aligned} \tag{4-3}$$

The distances for other intervals (D^2, D^3 … D^{11}) were obtained in the same way. The result is shown in column five of Table 4-7. With these numbers, the constant k could be calculated as follows:

$$\begin{aligned}
k &= 1\Big/\left(\frac{1}{D^1}+\frac{1}{D^2}+\cdots\frac{1}{D^{b-1}}+\frac{1}{D^b}+\frac{1}{D^{b+1}}+\cdots\frac{1}{D^m}\right) \\
&= 1\Big/\left(\frac{1}{0.306}+\frac{1}{0.245}+\frac{1}{0.221}+\frac{1}{0.221}+\frac{1}{0.221}+\frac{1}{0.221}+\frac{1}{0.306}+\frac{1}{0.245}+\frac{1}{0.930}+\frac{1}{0.221}+\frac{1}{0.245}\right) \\
&= 0.0235
\end{aligned} \tag{4-4}$$

The weight of each interval can then be obtained by k/D, as listed in the last column of Table 4-7. The interval bounds for the combined probabilities can be obtained through operations of the individual interval bounds. For example, the lower probability bound for the combined probability of the above example was:

$$L^{avg}=0\times0.077+0.01\times0.096+0.1\times0.106+0.1\times0.106+0.1\times0.106+0.1\times0.106+0\times0.077+0.01\times0.0962+0.66\times0.0253+0.1\times0.10+0.01\times0.096=0.073 \quad (4\text{-}5)$$

Same method applies for the combination of conditional probabilities for other nodes. The results of interval conditional probabilities after combination are shown in Appendix B. The combined interval conditional probabilities were used the parameters of the model for calculations and inferences, as will be discussed in Subsection 4.3.

4.2.4 Prior probabilities for nodes without parent nodes

For nodes without parent nodes, the conditional probabilities reduce to prior probabilities. Assumptions described in Table 4-8 were adopted for the prior probabilities in this study. Some of these assumptions were made from previous studies, and some from relative statistics, with Singapore Strait as the background for consideration. The prior probabilities used were point probabilities, even though they could also be represented with interval probabilities.

Table 4-8 Assumptions on the prior probabilities for nodes without parent nodes

Node	Prior probabilities	Description
Time of day	50% day; 50% night	-
Weather	49% Bad, 51% Good	Mean Rain days, 178days/365days from 1891-2014(124 years)
VTS Presence	100% Present, 0% Absent	Mandatory Ship Reporting System in the Straits of Malacca and Singapore, "STRAITREP"
Communication between ships	30% Yes; 70% No	Reference to (Linn Kathrin Fjæreide (PM) & Magnus S. Eide, 2006) for the node "Communication with another vessel"
Navigational complexity	80% High, 20% Low	Considering the high traffic density of Singapore strait
Safety culture	50% Good; 50% Bad	Reference to (Linn Kathrin Fjæreide (PM) & Magnus S. Eide, 2006)
Size of encounter ship	98% Big, 2% Small	Average percentage of small fishing vessels, tug/tow/government vessel and others from 2009-2014

4.3 Results and discussions

4.3.1 Computations with the interval BN

4.3.1.1 Marginal probabilities from the BN model

Unlike the traditional BNs which makes inferences with point probabilities, inferences in this study were made directly with the elicited interval probability parameters. Computations were performed with the GL2U algorithm, with the combined interval conditional probabilities as the baseline scenario. For comparison, the combined interval conditional probabilities were also converted to point probabilities, which were used for calculations with GeNie. The marginal probabilities calculated from the model with interval conditional probability parameters were also interval probabilities. The results were summarized in Table 4-9. Column 2 and 5 show the marginal probabilities computed with the traditional BN method, while Column 3 and 6 list the marginal interval probabilities obtained from the GL2U method.

Table 4-9 Comparison of the marginal probabilities from GL2U and GeNie

Nodes & states	Point	Interval	Nodes & states	Point	Interval
Pr(Collision=No)	0.406	[0.114, 0.641]	Pr(Maintenanceroutine1=NotFollowed)	0.447	[0.383, 0.510]
Pr(Collision=Yes)	0.594	[0.359, 0.886]	Pr(Maintenanceroutine1=Followed)	0.553	[0.490, 0.617]
Pr(VTSDetection=No)	0.062	[0.015, 0.109]	Pr(Resthours1=LessThanAdequate)	0.305	[0.201, 0.420]
Pr(VTSDetection=Yes)	0.938	[0.891, 0.985]	Pr(Resthours1=Adequate)	0.695	[0.580, 0.799]
Pr(Visibility=LessThanAdequate)	0.453	[0.376, 0.530]	Pr(Lookoutperson1=No)	0.457	[0.336, 0.582]
Pr(Visibility=Adequate)	0.547	[0.470, 0.624]	Pr(Lookoutperson1=Yes)	0.543	[0.418, 0.664]
Pr(Detection1=No)	0.011	[0.001, 0.034]	Pr(Updatingroutine1=NotFollowed)	0.430	[0.365, 0.495]
Pr(Detection1=Yes	0.989	[0.966, 0.999]	Pr(Updatingroutine1=	0.570	[0.505, 0.635]

Table 4-9 Comparison of the marginal probabilities from GL2U and GeNie (continued)

Nodes & states	Point	Interval	Nodes & states	Point	Interval
)			Followed)		
Pr(Manoeuvreplanning1=Incorrect)	0.398	[0.215, 0.623]	Pr(Visualdetection1=No)	0.340	[0.150, 0.566]
Pr(Manoeuvreplanning1=Correct)	0.602	[0.377, 0.785]	Pr(Visualdetection1=Yes)	0.660	[0.434, 0.850]
Pr(Manoeuvring1=Incorrect)	0.588	[0.413, 0.875]	Pr(Navigationalsystemdetection1=No)	0.387	[0.252, 0.553]
Pr(Manoeuvring1=Correct)	0.412	[0.125, 0.587]	Pr(Navigationalsystemdetection1=Yes)	0.613	[0.447, 0.748]
Pr(CompetenceoftheOOW1=Low)	0.466	[0.273, 0.691]	Pr(Distractionlevel1=Low)	0.509	[0.393, 0.658]
Pr(CompetenceoftheOOW1=High)	0.534	[0.309, 0.727]	Pr(Distractionlevel1=High)	0.491	[0.342, 0.607]
Pr(Steeringfailure1=No)	0.614	[0.490, 0.732]	Pr(Bridgeresourcemanagement1=Bad)	0.431	[0.357, 0.506]
Pr(Steeringfailure1=Yes)	0.386	[0.268, 0.510]	Pr(Bridgeresourcemanagement1=Good)	0.569	[0.494, 0.643]
Pr(Fatigue1=No)	0.670	[0.520, 0.810]	Pr(Crewtraining1=LessThanAdequate)	0.442	[0.370, 0.515]
Pr(Fatigue1=Yes)	0.330	[0.190, 0.480]	Pr(Crewtraining1=Adequate)	0.558	[0.485, 0.630]
Pr(Navigationalsystemsignal1=Bad)	0.251	[0.106, 0.439]	Pr(Navigationalsystemsettings1=Incorrect)	0.401	[0.199, 0.654]
Pr(Navigationalsystemsignal1=Good)	0.749	[0.561, 0.894]	Pr(Navigationalsystemsettings1=Correct)	0.599	[0.346, 0.801]

From Table 4-9, it can be observed that all point probabilities computed with the traditional BN method fall into the probability intervals obtained from the GL2U methods. The latter can also be visualized in Figure 4-7, where the red bars represented the interval probabilities. The wider the red bar, the higher the level of ambiguity or uncertainty associatd with the results. Some intervals were quite narrow. For example, the probability for “Detection=Yes” ranged from 0.966 to 0.999. Some others could be quite large. For example, the probability for “Collision=Yes” was somewhere between 0.359 and 0.886, varying from “Medium likelihood” to “Likely to happen”. For nodes without parent nodes, the marginal probabilities were the same with the point probabilities defined in 4.2.4.

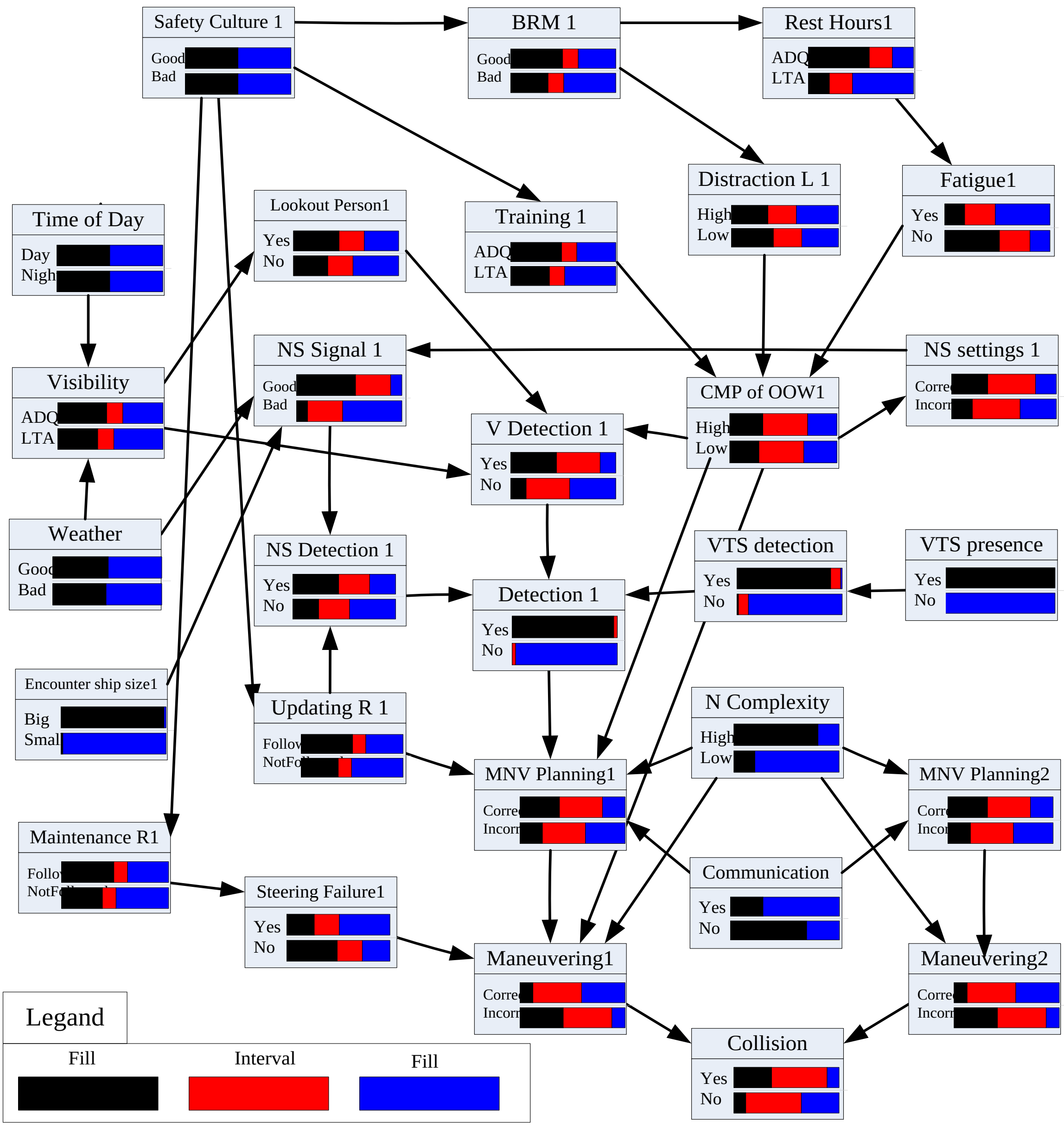


Figure 4-6 Interval marginal probabilities computed from the GL2U algorithm

Source (author)

The width of intervals could be partially explained by the definition of the linguistic terms. For example, the term medium likelihood corresponded to the interval [0.33, 0.66], which was quite wide already. This initial imprecision in the conditional probabilities sequentially propagated to the posterior probabilities. It might be advisable to employ more appropriate elicitation method in future research that allows more flexibility in defining the width of the intervals, such as the first version elicitation tool described in Section 4.2.1.1. However, the current elicitation method was adopted due to its straightforwardness and practical advantages.

4.3.1.2 Comparisons of results with inputs from different experts

In addition to the computation with the combined interval probabilities, separate calculations were also performed with the elicited interval CPTs from each of the eleven experts. The comparisons of marginal probabilities for six nodes (“Collision”, “Manoeuvring1”, “Detection1”, “Navigational system detection1”, “Visual detection1” and “VTS detection”) are shown in Figure 4-7.

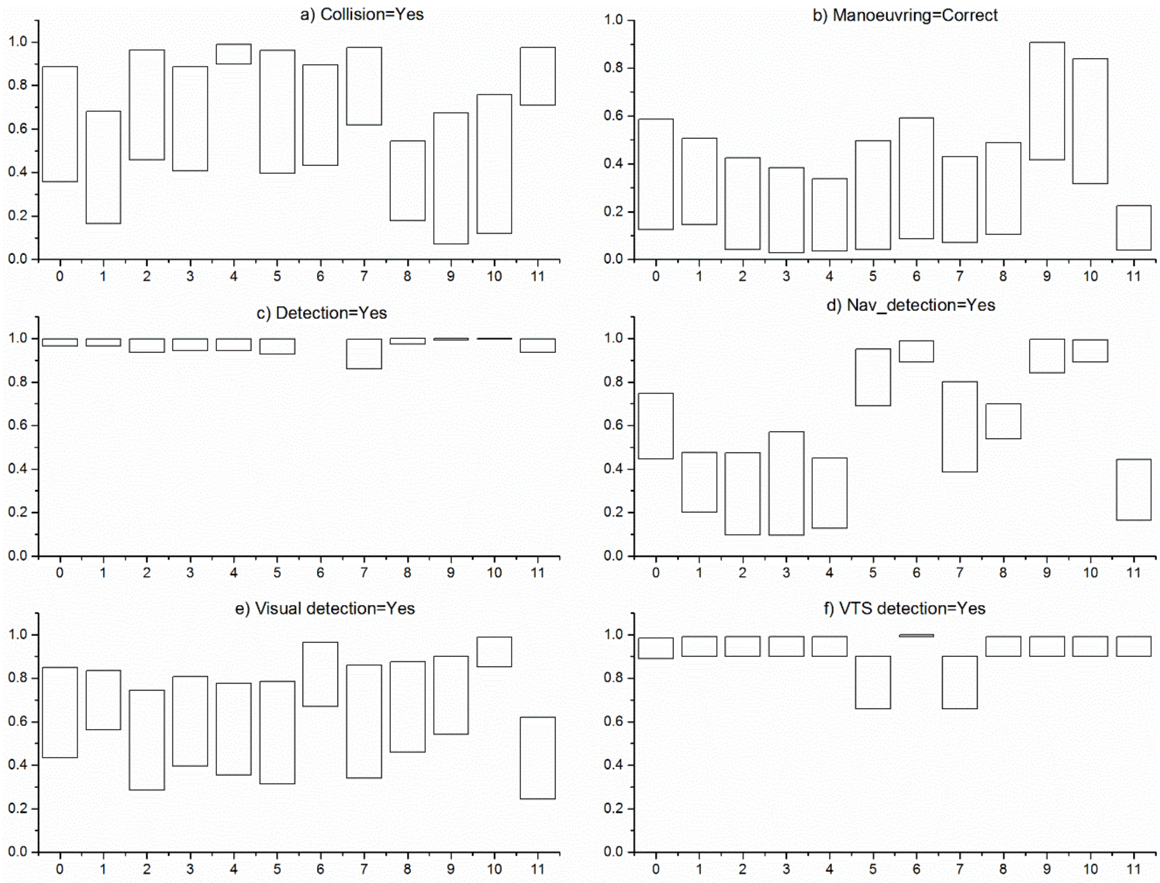


Figure 4-7 Comparisons of interval marginal probabilities with input from different experts

Source (author)

The X-axis refers to the expert number and Y-axis refers to the marginal probabilities. The number "0" denotes the baseline case with the combined interval conditional probability parameters.

According to Figure 4-7, the obtained marginal probability intervals from different experts were consistent for some nodes (e.g. "Detection"). But the results for other nodes showed different levels of discrepancies, both in the width and ranges of the intervals, which further verified the existence of epistemic uncertainty in the risk assessment result. This study is the first study to address the epistemic uncertainty quantitatively with interval probabilities in BN for maritime applications as far as we know. In future applications, careful attention should be paid to all steps of the risk assessment process, including the selection of experts, the education of experts on BN as well as the elicitation process to reduce the uncertainty.

4.3.2 Backward inferences with evidence

Back forward inference was performed by setting "Collision" as the evidence node. Changes of the posterior probabilities of some nodes with the evidence "Collision=Yes" and "Collision=No" are shown in Figure 4-8.

Unlike the traditional BN method where changes of the posterior probabilities could be measured directly, it was not easy to draw conclusion on the exact changes of the posterior probabilities with interval probabilities. Instead, we could only observe the differences of the probability bounds. From Figure 4-8, the biggest change in the probability bounds of the posterior probabilities was for the node "manoeuvring". Given the evidence "Collision=Yes", both the upper and lower bounds decreased significantly. On the other hand, there was a large increase in the probability bounds when the evidence was set as "Collision=No".

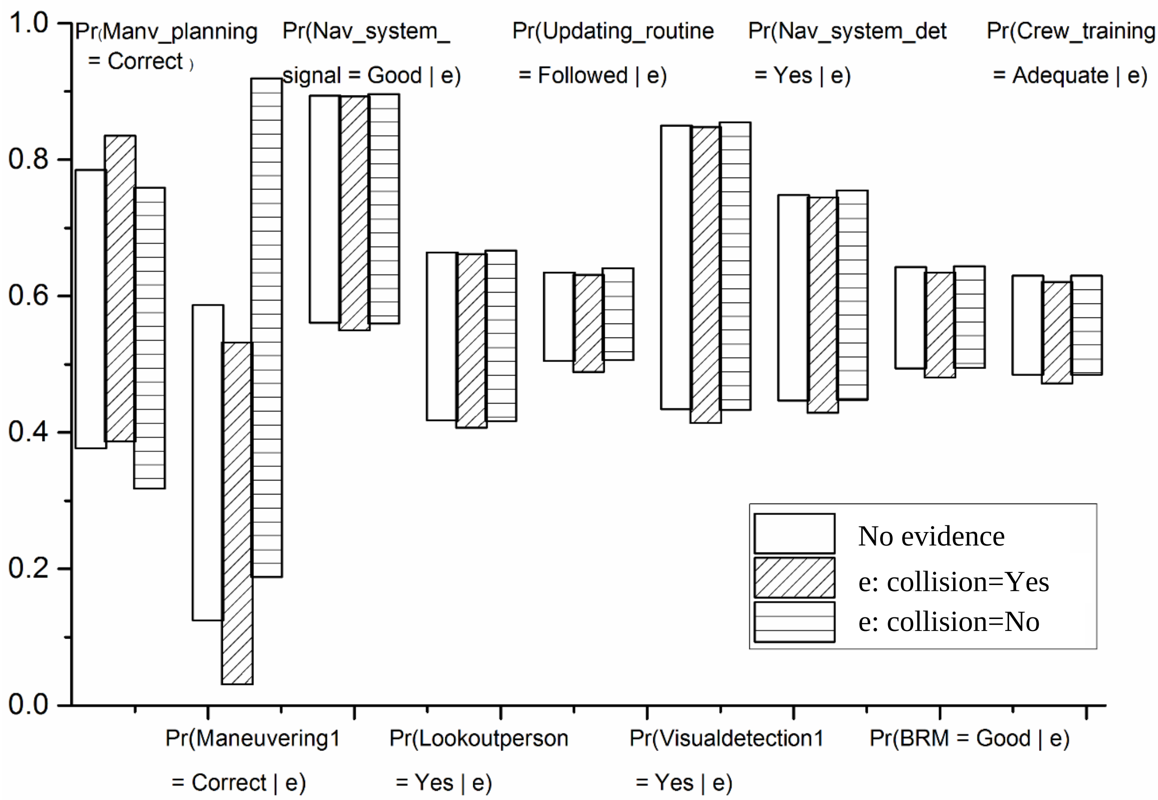


Figure 4-8 Changes of the interval posterior probabilities with evidences on the node "collision"

Source (author)

4.3.3 Model validations

4.3.3.1 Qualitative validations of the model

The validation framework described in Subsection 3.1.4 was used for the validation of the present BN model. The first aspect to focus was the nomological validation, which checked whether the model fit a wider domain. On this aspect, the causation probability model fit well in the literature of maritime safety modelling as well as maritime risk assessment. It was also in line with other causation models for ship collisions. As to face validation, the present model was thought to be appropriate. It included different types of casual factors, particularly the human and organizational factors, which accounts for most collision accidents. During the elicitation process, the experts showed acknowledgement to the causal relations represented in the model. No changes were suggested. Content validation ensures that all and only the relevant factors are included in the model. It was argued here that the major causal factors were included even though they were not meant to be exhaustive.

Concurrent validation, convergent validation and discriminant validation focuses on comparisons of the current model with the nomologically proximal or distal. These three aspects are discussed interchangeably below by comparing the present model with the model built in (Friis-Hansen & Simonsen, 2002) and (Det Norske Veritas, 2003). In fact, the current model adopted the same logic with (Friis-Hansen & Simonsen, 2002): two sets of same nodes and causal relations were used corresponding to each ship; collision was modelled as the result of the manoeuvring action of both ships; common factors such as the “weather” “traffic condition” exerted influence on both sets of nodes. Factors regarding the human performance, navigational system as well as safety culture were adopted in the present model, similar to the two previous studies, even though the mentioned literature looked into more details. For example, the navigational system referred in the present model was specified as the radar system and the AIS in (Det Norske Veritas, 2003). All nodes in the present model were binarized to ease the elicitation workload. The binarized states such as “Yes” “No”, “Adequate” “Less than adequate”, covered the full scales of the possible outcomes for all nodes.

The predictive validation for the present model is discussed below. First, it should be noted that the degree to which the risk numbers produced in this study are accurate compared to the underlying true risk (Aven & Heide, 2009) will not be discussed, since true risk is not an issue for the LP-HC accidents (Rosqvist, 2010). The collision causation probability obtained from the present model should be interpreted per the linguistic terms used for probability elicitation, rather than to its true probability in the power of e^{-4} as reported in (Det Norske Veritas, 2003). This is in line with (Y. F. Wang et al., 2010) (J Ren et al., 2009). As Rosqvist (2010) puts it, validation of risk analysis is not a property of the risk model but a property of the decision context. Obtaining the absolute risk number doesn't add much value. In the context of decision making as will be discussed in the next Subsection, it is the relative changes in the risk level that matters.

4.3.3.2 Sensitivity analyses for the BN model

The marginal interval probabilities of the BN model with the interval parameters are quite insensitive to evidences, as reflected by Figure 4-8. Here, the analysis of sensitivity to findings and sensitivity to parameters are analysed for the BN model with the point probabilities.

a) Sensitivity to findings

Table 4-10 shows the mutual information between the node "collision" and all other nodes. The three most informative nodes are "Manoeuvring" "Manoeuvre planning" and "Competence of the OOW", implying that it is most important to observe the true states for these three nodes to determine the collision probability.

Table 4-10 Mutual information between the node "collision" and all other nodes

Node	VOI	Node	VOI
Manoeuvring	3.77E-02	Visual detection	2.40E-03
Manoeuvre planning	1.85E-02	Navigational system detection	2.28E-03
Competence of the OOW	1.35E-02	Navigational system signal	2.06E-03
Navigational system settings	7.98E-03	Navigational complexity	1.76E-03
Safety culture	5.18E-03	Look out person	1.50E-03
Crew training	4.73E-03	Communication between ships	1.04E-03
Bridge resource management	4.71E-03	Detection	3.26E-04
Fatigue	4.45E-03	VTS Detection	2.63E-05
Maintenance routine	4.06E-03	Visibility	2.11E-07
Rest hours	3.89E-03	Weather	1.20E-07
Steering failure	3.52E-03	Time of day	6.40E-09
Updating routine	3.08E-03	Size of encounter ship	1.42E-09
Distraction level	3.06E-03	VTS Presence	3.50E-10

b) Sensitivity to parameters

Table 4-11 shows the maximum sensitivity values for each node. Since more than one sensitivity value exist for each node, corresponding to each parameter/conditional probability number, the states of the parent nodes that produce the maximum sensitivity values are also listed in the table.

Table 4-11 The maximum sensitivity values for different nodes and the corresponding parents' states

Node	Max$\lvert c_1 \rvert$	π (combination of states of the parent nodes)
Collision	3.50E-01	Incorrect manoveuvring of both ships
Manoeuvreing	1.05E-01	Correct manoveuvre planning; No steering failure; Highly competence OOW, High Navigational complexity
Detection	9.87E-02	Navigation system detection; Visual detection; VTS detection
Manoeuvre planning	9.24E-02	Detection; High navigational complexity; Highly competent OOW; No communication between two ship
Fatigue	8.26E-02	Good BRM
Competence of the OOW	7.84E-02	Adequate training; Not fatigued; Low distraction level
Rest hours	6.14E-02	Good BRM
Steering failure	4.91E-02	Maintenance routine followed
BRM	4.83E-02	Good safety culture
Crew training	4.72E-02	Good safety culture
Maintenance routine	3.15E-02	Good safety culture
Distraction level	2.58E-02	Good BRM
VTS Detection	2.24E-02	VTS present
Navigational system detection	1.06E-03	Updating routine followed; Good signal on navigational system
Visual detection	6.87E-04	Reduced visibility; Highly competence OOW; Look out person present
Updating routine	6.85E-04	Good safety culture
Navigational system signal	3.49E-04	Bad weather; Correct settings of navigational system; The other ship is big
Navigational system settings	2.56E-04	Highly competence OOW
Visibility	2.25E-04	Bad weather; Daytime/Night
Look out person	2.01E-04	Reduced visibility; Good BRM

Note that the absolute sensitivity values for each state of the examined nodes are identical since all nodes are binary. The rank of the most sensitive variables in Table 4-11 is similar to the analysis by Hänninen and Kujala (2012). The BN model was most sensitive to the parameters of the node “Collision” and “Manoeuvreing”, whose conditional probabilities could be found in Table B1 and Table B2 in Appendix B. A closer examination of Table B1 and Table B2 showed theoretical validity.

4.4 Decision making for risk management under uncertainty with interval probabilities

Uncertainty in the result of the risk assessment also propagates to the decision-making process and influences the ranking of potential RCOs. A simple analysis is conducted below to illustrate how the ranking of RCOs changes when the uncertainty is taken into account.

4.4.1 Cost and benefit analysis method

Cost-benefit analysis is the fourth step for a complete FSA study. The two most common measures for the evaluation of RCOs are Gross Cost of Averting a Fatality (GCAF) and Net Cost of Averting a Fatality (NCAF), which are defined as follows (Kontovas & Psaraftis, 2009) (Psaraftis, 2012):

$$GCAF = \frac{\Delta C}{\Delta R} \tag{4-6}$$

$$NCAF = \frac{\Delta C - \Delta B}{\Delta R} \tag{4-7}$$

where: ΔC is the cost per ship for implementing the RCO;

ΔB is the economic benefits resulting from the implementation;

ΔR is the risk reduction effect per ship.

The cost for implementation includes the initial installation cost as well as the running cost for operations. This value does not vary significantly for different type of ships, see

(Linn Kathrin Fjæreide, 2006). Calculation of the benefit values is more intricate, which consists the direct savings from the cargo damage, ship repairs, delays and off-hire, pollutions and clean up, as well as the long-term effect on the company reputation and tourism. This value is related to the ship particulars and the accident location. Normally, the cost and benefit values are obtained on annual basis first and then converted to Net Present Values (NPV) under specific interest rates. The level of risk reduction ΔR, on the other hand, are normally obtained from the BN model. The three million criterion is normally used for accepting or rejecting a potential RCO.

4.4.2 Subjective method for the evaluation of RCOs

It is always very difficult to obtain the absolute cost and benefit values. Even with many assumptions, the values are still subject to various levels of uncertainty. Compared with traditional methods, the subjective method proposed by Y. F. Wang et al. (2013) is more practical. It is more concerned with the ranking of the RCOs while the traditional method is more focused on the evaluation of individual RCOs. Instead of based on the absolute cost and benefit values, the subjective method describes cost (benefit) in terms of membership to seven categories, as in Table 4-12.

Table 4-12 Cost expressions

Linguistic terms	1	2	3	4	5	6	7
Very high	0	0	0	0	0	0.75	1
High	0	0	0	0	0.75	1	0.25
Moderately high	0	0	0	0.5	1	0.25	0
Average	0	0	0.5	1	0.5	0	0
Moderately low	0	0.25	1	0.5	0	0	0
Low	0.25	1	0.75	0	0	0	0
Very low	1	0.75	0	0	0	0	0

For simplification, GCAF index is used in the following example where only cost values will be evaluated. Suppose that the cost value of the i^{th} RCO is:

$$C_i = \left[\mu_{C_i}^1/1, \mu_{C_i}^2/2, \mu_{C_i}^3/3, \mu_{C_i}^4/4, \mu_{C_i}^5/5, \mu_{C_i}^6/6, \mu_{C_i}^7/7,\right] \tag{4-8}$$

where $\mu_{C_i}^n$ refers to the degree to which C_i belongs to the n^{th} category.

C_i can also be evaluated in terms of the utility expression, as defined in Table 4-13.

Table 4-13 Utility expressions

Linguistic terms	1	2	3	4	5	6	7
Slightly preferred	0	0	0	0	0	0.75	1
Moderately preferred	0	0	0	0.5	1	0.25	0
Preferred	0	0.25	1	0.5	0	0	0
Greatly preferred	1	0.75	0	0	0	0	0

If $U_{C_i}^j$ refers to the degree to which C_i belongs to the j^{th} utility expression, then:

$$U_{C_i}^j = \frac{\alpha_{ij}}{\sum_{j=1}^{4} \alpha_{ij}} \quad (j = 1,2,3,4) \tag{4-9}$$

where α_{ij} is the reciprocal relative distance between C_i and the j^{th} utility expression.

$$\alpha_{ij} = \frac{1}{d_{ij}/d_H} \quad (j = 1,2,3,4) \tag{4-10}$$

where d_{ij} is the Euclidean distance between C_i and the j^{th} utility expression, and d_H is the minimum value of d_{ij}. If d_H =0, then α_{ij} is defined to be 1.

$$d_{ij} = \left(C_i, U_j\right) = \left(\sum_{j=1}^{4} \left(\mu_{C_i} - \mu_u^j\right)^2\right)^{1/2} \tag{4-11}$$

The preference degree P of any RCOs can then be calculated from the following functions (Y. F. Wang et al., 2013):

$$p_i = \sum_{j=1}^{4} U_C^j \times K_j + \left(1 - \sum_{j=1}^{4} U_C^j\right) \times \frac{1}{4} \times \sum_{j=1}^{4} K_j \tag{4-12}$$

where $[K_1, K_2, K_3, K_4]=[0.217, 0.478, 0.739, 1]$.

The final ranking is dependent on $RP_i=1/(P_i \times \Delta R)$. The smaller RP_i is, the more cost effective the RCO will be.

4.4.3 Evaluation of the RCOs developed for the current model

Four RCOs were proposed based on the analysis with the present BN model. (1) Use of simulator training for the officers on difficult tasks, such as passage planning and operations during malfunction of critical technical equipment. (2) Improvement of the BRM for the bridge team. (3) Redundant propulsion or steering system (4) Improvement of the safety culture. Changes in the collision probabilities after implementing these RCOs were calculated with the traditional BN and the interval BN separately, as shown in Table 4-14. For the calculation with the interval BN, changes of the upper and lower bound of posterior probabilities were used as two special cases for comparisons.

Table 4-14 Risk reduction effect for each RCO using BN with point and interval probabilities

RCOs	Lower bound	Upper bound	Point Probability	Change of Lower bound	Change of Upper bound	Change of Point Probability
RCO1	0.273	0.839	0.529	0.086	0.047	0.064
RCO 2	0.274	0.838	0.531	0.085	0.048	0.063
RCO 3	0.313	0.865	0.544	0.046	0.021	0.049
RCO 4	0.271	0.835	0.518	0.088	0.051	0.076

Suppose that the cost of these four RCOs are “Moderately High” “High” “Average” “Very high” and varies around them (J. Wang, Yang, & Sen, 1996), where the estimated cost values are as follows:

Table 4-15 Cost values for the RCOs in the present model

RCOs	1	2	3	4	5	6	7
RCO1	0	0	0	0.6	1	0.5	0
RCO 2	0	0	0	0	0.7	1	0.4
RCO 3	0	0	0.55	1	0.45	0	0
RCO 4	0	0	0	0	0	0.6	1

The preference degree calculated for RCO1 to RCO4 with the best fit method described in subsection 4.4.2 were 0.531, 0.532, 0.614 and 0.328 respectively. Combining with the risk reduction values from Table 4-12, i.e. “Change of lower probability bound (case 1)”, “Change of upper probability bound (case 2)”, and “Change of point Probability” (case 3), the following RP values and rankings of the four RCOs were obtained, as in Table 4-16.

Table 4-16 The RP values and ranking of the four RCOs for different cases

	RCO1	RCO2	RCO3	RCO4	Rankings
Case1	21.889	22.124	35.418	34.622	RCO1, RCO2, RCO4, RCO3
Case2	40.052	39.178	77.581	59.740	RCO2, RCO1, RCO4, RCO3
Case3	29.280	29.990	33.038	40.276	RCO1, RCO2, RCO3, RCO4

The ranking for different RCOs varied depending on the risk reduction values adopted, indicating the way of impact of the uncertainty in the risk analysis result on the decision-making process.

Historically, shipping has been an industry where the risks of injury and death are considerably high for the crew (Bloor, Thomas, & Lane, 2000). The fatality rate of merchant shipping was more than 10 times higher than the onshore industries according to a study on the Danish fleet (H. Hansen et al., 2002). The number was even higher for the British fleet where the mortality rate was 21 times of the general workplace, 4.7 times of construction industry and 13 times of the manufacturing industry (Roberts, Nielsen, Kotłowski, & Jaremin, 2014). In addition to the high rate of fatal accidents, high frequency of non-fatal occupational accidents was also observed. In a Finnish study, the rate of non-fatal injuries on board was close to the rate for the whole population (Jensen et al., 2005). According to a big scale international survey, the average injury rate for was 9% during the respondents' latest tour of duty (Olaf Chresten Jensen, Jens Fyhn Lykke Sørensen, et al., 2004).

Once on board of ships, seafarers are exposed to many hazards within the harsh working environment (noise, vibration etc.). Their health and safety is subjected to various occupational accidents, as well as possible shipping accidents. In addition, reduced manning level, long working hours and excessive work load all further contribute to their occupational risk. At present, detailed management procedures have already been implemented in most shipping companies. However, despite the effort, the job safety on board merchant ships remains an area with much room for improvement. A big gap still exists between the best and worst practices (Bloor et al., 2000). It should be noted that improving the job safety and reducing the occupational injuries are of great importance not only to the seafarers themselves but also of direct benefit to shipping companies by reducing the insurance premiums as well as liabilities and legal costs. The number/frequency of loss time injuries together with the number/frequency of accidents, incidents and near misses are also safety performances indicators for many shipping companies (Grabowski, Ayyalasomayajula, Merrick, & Mccafferty, 2007) (Card, Baker, McSweeney, & McCafferty, 2005). However, despite the importance, only a few studies have been conducted on the analysis of seafarers' occupational health and safety risks so far (Ellis et al., 2010). A detailed literature review on the existing studies has been presented in Chapter 2. The present study aims to develop a quantitative model that could assess the probability of seafarers' injuries so as to provide decision support for safety management.

5.1 Influencing factors for workplace accidents and injuries

An extensive number of papers on occupational accidents and injuries from different sectors were reviewed to identify potential risk factors. Table 5-1 compiles the lists summarized from a few representative papers. This list is not meant to be exhaustive, but has covered the recurring ones.

The questionnaire used for the survey was designed based on Table 5-1. However, not all factors in Table 5-1 were included, since it is difficult to collect information on some factors, for example "market influence". Meanwhile, multiple questions were designed for some other factors. For example, four questions were set regarding Personal Protective Equipment (PPE), covering aspects on "PPE availability", "PPE training", "PPE usage" and "Reasons that hinder PPE usage". The survey intends to identify the specific areas on PPE that is important.

Information on nationality was collected for record purpose only. Even though lower injury rates have been observed for some nationalities (e.g. Filipinos) compared to others (e.g. Europeans) (Jensen, 2009) (H. L. Hansen et al., 2008) (Carter, 2011) (Ádám, 2013) (Grøn & Knudsen, 2012), there is insufficient evidence to support that a seafarer's nationality determines his safety practice (Grøn & Knudsen, 2012). The difference in injury rates among different nationalities can be explained with disparities found in tour duration, proportion of officers, age structure, safety standard, work activities as well as their reporting behaviour and social care (Jensen, 2009) (Ádám, 2013). Table 5-2 lists the potential risk factors included in the questionnaire and the corresponding categories.

Table 5-1 Summary of factors that influence the risk of occupational accidents and injuries

Factors	1	2	3	4	5	6	7	8	9	10	11	12	13
Gender										√	√	√	
Age	√					√			√	√	√	√	
Experience		√				√	√		√	√			
Position	√									√	√	√	
Nationality*	√									√			
Ship type	√												
Change of ship	√												
Time doing the job	√									√	√		
Shift hours						√					√	√	
Stress and Fatigue		√	√	√									
Training		√	√	√	√	√	√	√		√		√	
Fitness			√	√		√		√	√				
Lack of attention		√		√									
Risk perception		√			√					√			√
Safety Procedure			√	√				√				√	
Non-compliance				√								√	
Housekeeping		√											√
Quality of hardware		√		√							√	√	
Personal protective equipment (PPE)		√	√	√	√							√	√
Weather		√	√				√		√				
Environment condition					√	√		√					
Inspection/Maintenance		√						√					
Safety culture		√	√								√		
Management and Supervision		√					√	√			√		√
Accident feedback loop		√											
Knowledge			√				√				√	√	
Motivation			√	√				√					
Market influence		√	√										

1. (H. Hansen et al., 2002) 2. (HSE, 2002) 3. (D Attwood et al., 2006; Daryl Attwood et al., 2006) 4. (Maurizio Bevilacqua, Ciarapica, & Mazzuto, 2012) 5. (Mure, Demichela, & Piccinini, 2006) 6. (McCauley-Bell & Badiru, 1996a, 1996b) 7. (Lee & Halpin, 2003) 8. (M Bevilacqua et al., 2008) 9. (Dumrak et al., 2013) 10. (Rivas et al., 2011) 11.(Smith & DeJoy, 2012) 12. (PERSONA, BATTINI, FACCIO, BEVILACQUA, & CIARAPICA, 2006) 13. (Matías et al., 2008)

Table 5-2 Risk factors and their states used in the questionnaire

Factors	Categories for each factor
Gender	Male; Female
Age	<25 years; 25-34 years; 35-44 years; 45-55 years; >55 years
Sea service (experience)	<2 years; 2-5 years; 6-10 years; 11-20 years; >20 years
Nationality	-
Ship type	Tanker; Container; Bulk carrier; General cargo; Passenger ship; Other
Position	Senior deck Officer; Junior deck Officer; Deck ratings; Senior Engineer; Junior Engineer; Engine ratings; Catering
Time in position	-
Duty duration	<=6 months; 7-12 months; >12 months
Change of ship	Yes; No
Familiarity	Very unfamiliar; Unfamiliar; Medium; Familiar; Very familiar
Training	Very ineffective; Ineffective; Medium; effective; Very effective
Adequate rest hours	Always; Sometimes; Seldom or never
Distraction	Repetitive task; Isolated surroundings; Ship vibration/noise; Work pressure; Fatigue; None
Job risk awareness	Yes, always; Yes, sometimes; Seldom or never
Job Risk assessment	Yes, for all tasks; Yes, for non-routine tasks; Seldom or never
Risk communication	Yes, always; Yes, sometimes; Seldom or never
Procedure design	Strongly disagree; Disagree; Neutral; Agree; Strongly agree
Shortcut	Always; Sometimes; Seldom or never
House keeping	Very bad; Bad; Medium; Good; Very good
Defective hardware	Always; Sometimes; Seldom or never
PPE availability	Always; Sometimes; Seldom or never
PPE training	Yes; No
PPE usage	Always; Sometimes; Seldom or never
Not using PPE	Unnecessary; Efficiency; Uncomfortable; Not available; Other
Shore visit frequency	No visit; Once a year; Twice a year; More than twice a year
PMS execution	Very bad; Bad; Medium; Good; Very good
Accident feedback	Always; Sometimes; Seldom or never
Injury	Never; Once; Twice; More than twice

The actual questionnaire is attached in Appendix C. Overall, most questions in the questionnaire are multiple choice questions. Respondents were asked to answer all questions based on their latest tour of duty. From the initial version, several master mariners in Singapore were consulted, and subsequent modifications on the questionnaire were made based on their suggestions.

5.2 Data collection method

5.2.1 Design of the survey questionnaire

To reduce the uncertainty with experts' judgment, the data source for the study of seafarer injuries came from an empirical survey. The questionnaire was designed based on a literature review about the potential risk influencing factors. More information can be found in Section 5.1. The respondents were asked to answer the questions based on their latest tour of duty anonymously to encourage honest answers. From the initial version, several master mariners in Singapore were consulted, and subsequent modifications were made to the questionnaire based on their suggestions. The final version of the questionnaire contained 28 questions (can be found in Appendix C), collecting information on the demographic composition, the seafarer's personal factors, his/her working behavior as well as the management practice on board.

5.2.2 Questionnaire administration

The survey was conducted in the four Asian countries of Singapore, China, South Korea and Vietnam given their representation in the international seafaring market. All seafarers with sailing experience were eligible for the survey. To reach out to as many potential respondents as possible, various channels were explored, including online forums, training department in maritime institutes, seafarers' organizations as well as individual shipping companies. In addition to the original English questionnaire, there were three translated versions of questionnaire to make it easier for different ethnic groups, i.e. the Chinese version, Korean version and Vietnamese version. Google form was used as the main platform for the online survey. However, since seafarers in China could not get access to google, the Chinese online survey platform 'sojump.com' was used. The printed paper questionnaires were used as a supplementary alternative. The data collection process spanned around the five-month period from Nov 2015 to Mar 2016. Eventually, a total of 354 responses were received.

5.3 Summary statistics from the survey

5.3.1 Respondents' profile

The survey was anonymous. Distributions of the respondents' profiles regarding the demographic factors: "Gender" "Age" "Years of experience" "Nationality" "Ship type" "Position" "Time in position", are presented in Figure 5-1.

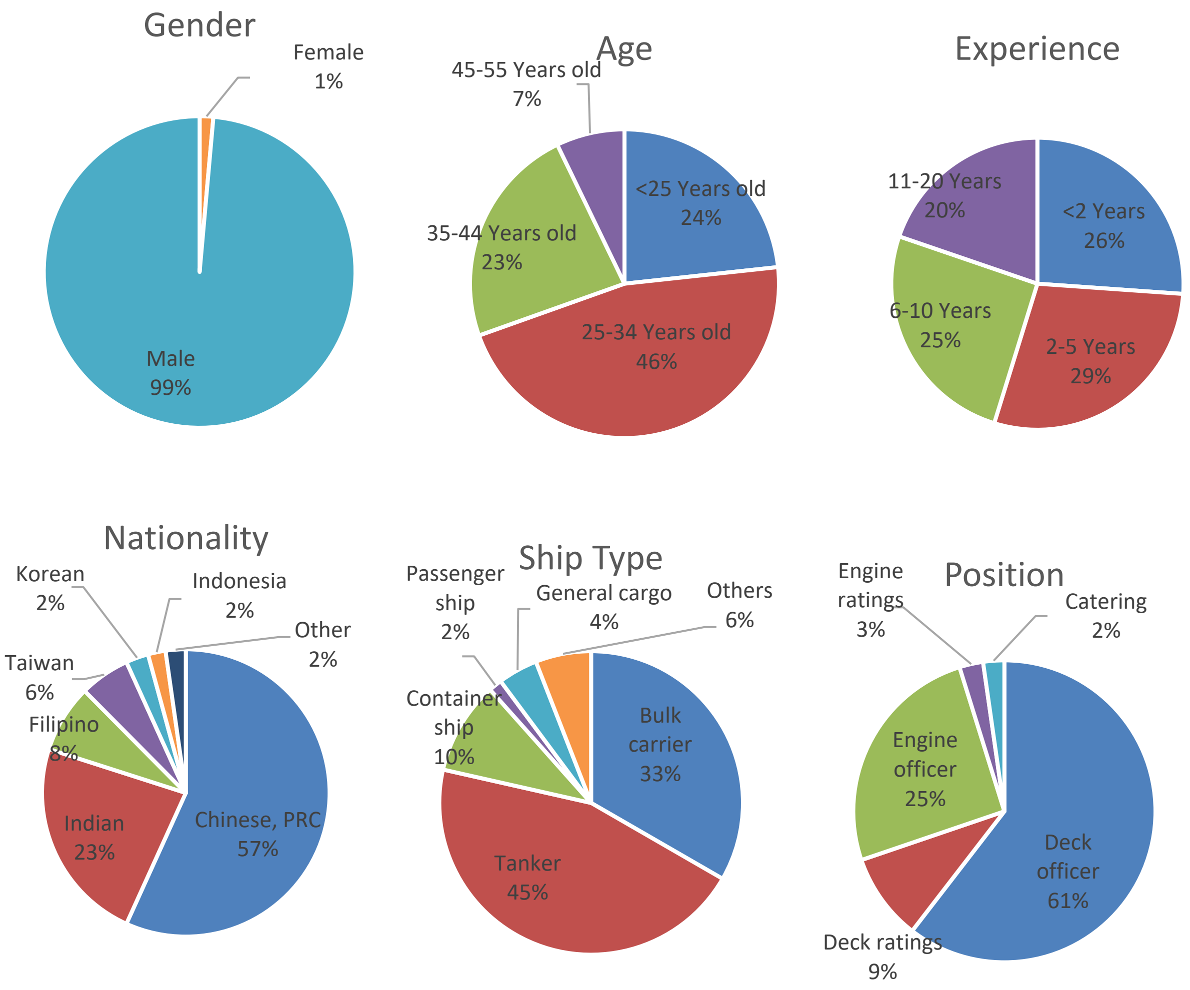


Figure 5-1 Respondents' profiles of the survey on seafarers' injuries at work

Source (author)

5.3.2 Data summaries from the survey

51 out of the 354 responses in the survey indicated at least one injury during the latest tour of duty, giving an overall injury rate of 14.41%, which was higher than the overall injury of 9.1% reported in (Olaf Chresten Jensen, JFL Sørensen, et al., 2004) but was quite close to the injury rate of 14.4% for the Chinese seafarers reported in the same study. This can be partially explained by the high proportion of Chinese seafarers among the respondents in the present study. Six seafarers got injured twice, and another six were injured more than twice, as in Table 5-3.

Table 5-3 Information on injury records collected from the surveys

Times of injury	Number
Never	303
Once	39
Twice	6
More than twice	6
Grand Total	354

Table 5-4 shows the contingency table of the injury history versus each risk factor included in the questionnaire. The original categories of injuries “Once” “Twice” “More than twice” were combined into the new group “At least injured once”, which is referred to as the “Injury cases” in Table 5-4. Injury rates for each category of the risk factors are shown in the last column of Table 5-4. The percentage of the surveyed population for each category is presented in the second last column. The following preliminary observations could be obtained from Table 5-4:

- Higher injury rates were observed for younger seafarers except for the group of seafarers “>55 years old”. The injury rate for seafarers “<25 Years old” was as high as 22%, significantly higher than 8% for “35-44 Years old” and “45-55 Years old”.

Table 5-4 Contingency tables for the injury records per individual risk factors

Factors	Categories	Never injured	Injury cases	Total cases	Population percentage	Injury rates
Gender	Female	4	1	5	1%	20%
	Male	299	50	349	99%	14%
Age	<25 Years old	61	17	78	22%	22%
	25-34 Years old	132	23	155	44%	15%
	35-44 Years old	72	6	78	22%	8%
	45-55 Years old	22	2	24	7%	8%
	>55 Years old	16	3	19	5%	16%
Experience	<2 Years	67	15	82	23%	18%
	2-5 Years	75	15	90	25%	17%
	6-10 Years	66	14	80	23%	18%
	11-20 Years	57	5	62	18%	8%
	>20 Years	38	2	40	11%	5%
Nationality	Chinese	175	26	201	57%	13%
	Indian	66	16	82	23%	20%
	Filipino	23	4	27	8%	15%
	Taiwan	18	2	20	6%	10%
	Korean	7	2	9	3%	22%
	Indonesian	7	0	7	2%	0%
	Others	7	1	8	2%	13%
Ship type	Bulk carrier	102	16	118	33%	14%
	Tanker	136	24	160	45%	15%
	Container ship	32	3	35	10%	9%
	General cargo	14	1	15	4%	7%
	Passenger ship	3	2	5	1%	40%
	Others	16	5	21	6%	24%
Position	Deck officer	188	26	214	60%	12%
	Deck ratings	28	5	33	9%	15%
	Engine officer	73	17	90	25%	19%
	Engine ratings	6	3	9	3%	33%
	Catering	8	0	8	2%	0%
Tour duration	<=6 months	128	25	153	43%	16%
	7 to 12 months	150	23	173	49%	13%
	>12 months	25	3	28	8%	11%
Change of ship	Yes	127	25	152	43%	16%

Table 5-4 Contingency tables for the injury records per individual risk factors (continued)

Factors	Categories	Never injured	Injury cases	Total cases	Population percentage	Injury rates
Familiarity	No	176	26	202	57%	13%
	Very unfamiliar	5	1	6	2%	17%
	Unfamiliar	4	2	6	2%	33%
	Moderate	27	3	30	8%	10%
	Familiar	171	31	202	57%	15%
	Very familiar	96	14	110	31%	13%
Adequate training	Strongly disagree	6	2	8	2%	25%
	Disagree	19	6	25	7%	24%
	Neutral	50	9	59	17%	15%
	Agree	186	29	215	61%	13%
	Strongly agree	42	5	47	13%	11%
Adequate rest	Seldom	14	3	17	5%	18%
	Sometimes	88	19	107	30%	18%
	Always	201	29	230	65%	13%
Distractions*	Repetitive tasks	17	94	111	31%	15%
	Isolated surround	15	80	95	27%	16%
	Ship vibration etc.	14	76	90	25%	16%
	Work pressure	24	126	150	42%	16%
	Fatigue	24	129	157	44%	15%
	None of the above	10	95	105	30%	10%
Risk awareness	No, seldom	4	1	5	1%	20%
	Yes, sometimes	45	11	56	16%	20%
	Yes, always	254	39	293	83%	13%
Risk assessment	No, seldom	17	3	20	6%	15%
	Yes, but only for non-routine tasks	103	21	124	35%	17%
	Yes, for all tasks	183	27	210	59%	13%
Risk discussion	No, seldom	20	3	23	6%	13%
	Yes, sometimes	73	20	93	26%	22%
	Yes, always	210	28	238	67%	12%
Procedure design	Strongly disagree	13	0	13	4%	0%
	Disagree	5	5	10	3%	50%
	Neutral	53	11	64	18%	17%
	Agree	204	31	235	66%	13%

Table 5-4 Contingency tables for the injury records per individual risk factors (continued)

Factors	Categories	Never injured	Injury cases	Total cases	Population percentage	Injury rates
	Strongly agree	28	4	32	9%	13%
Short cut	Seldom or never	106	11	117	33%	9%
	Sometime	161	39	200	56%	20%
	Always	36	1	37	10%	3%
Housekeeping	Very bad	1	0	1	0%	0%
	Bad	6	1	7	2%	14%
	Moderate	64	15	79	22%	19%
	Good	163	24	187	53%	13%
	Very good	69	11	80	23%	14%
Defective tools	Seldom	140	21	161	45%	13%
	Sometimes	131	29	160	45%	18%
	Always	32	1	33	9%	3%
PPE availability	Seldom	205	20	225	64%	9%
	Sometimes	89	29	118	33%	25%
	Always	9	2	11	3%	18%
PPE training	No	10	5	15	4%	33%
	Yes	293	46	339	96%	14%
PPE usage	Seldom or never	6	2	8	2%	25%
	Sometime	39	8	47	13%	17%
	Always	258	41	299	84%	14%
Shore visit	No visit	5	3	8	2%	38%
	Once in a year	72	14	86	24%	16%
	Twice in a year	81	16	97	27%	16%
	More than twice in a year	145	18	163	46%	11%
Maintenance	Very bad	2	0	2	1%	0%
	Bad	4	1	5	1%	20%
	Moderate	71	18	89	25%	20%
	Good	160	23	183	52%	13%
	Very good	66	9	75	21%	12%
Feedback loop	Seldom	6	2	8	2%	25%
	Sometime	38	19	57	16%	33%
	Always	259	30	289	82%	10%

* Allows multiple answers

- Equal injury rates (18%) were observed for the experience group "<2 Years" "2-5 Years" and "6-10 Years". The number drops to 8% and 5% for the more experienced groups "11-20 Years" and ">20 Years" respectively. Seafarers with previous experience on the same ship or its sister ships had a slightly lower injury rate than those without such experience.
- Indian seafarers had a considerably higher injury rate than others. Meanwhile, lower injury rates were observed for container and general cargo ship.
- No injuries were reported by seafarers from the catering department. Engine ratings had the highest injury rate (33%) followed by the engine officers (19%). Deck officers had the lowest injury rate (12%). The overall injury rate (20.2%) for the engine department was considerably higher than the deck department (12.6%). As to the rank, the injury rate of ratings was higher (19%) than of the officers (14%).
- The tour duration for most (49%) of the respondents were "7 to 12 months", followed by 43% short tour durations of "<6 months". Very few (8%) had very long tour duration of over 12 months. The injury rates, however, didn't show increase with the increase in tour duration as claimed by (Olaf Chresten Jensen, JFL Sørensen, et al., 2004).
- 74% respondents (strongly) agree that their company provided adequate training. The injury rate for them was around 13%. Meanwhile, for those who (strongly) felt a lack of training, an injury rate of 24% was observed. Respondents who always had sufficient rest reported lower injury rates.
- 70% respondents reported to have been distracted by some sources at work. The top two source of distractions were fatigue (44%), and work pressure (42%). People who reported no distractions had a lower injury rate of 10%.
- The injury rates for respondents who always had risk awareness and always discussed risks were much lower (13%) than those who did not (20%). Taking shortcut was

found common, with 67% of the respondents reported sometimes or always doing so. Meanwhile, the injury rate decreased from 18% to 13% when housekeeping condition improved from substandard to good/very good.

- The injury rates varied a lot depending on “PPE availability”, “PPE training” and “PPE usage”. When PPE was seldom unavailable, the injury rate was as low as 9%, which increased to 24% when the unavailability of PPE was sometimes or always. For respondents without PPE training, the injury rate was as high as 33%. Similarly, for the small group who seldom used PPE at work, the injury rate was 25%. Figure 5-2 shows the factors that hinder PPE usage. Impacts on efficiency was observed to be the number one reason, followed by PPE availability. Other reasons specified by the respondents include omission, laziness, quality of the PPE, or when the task was repetitive or considered to be at low risk.

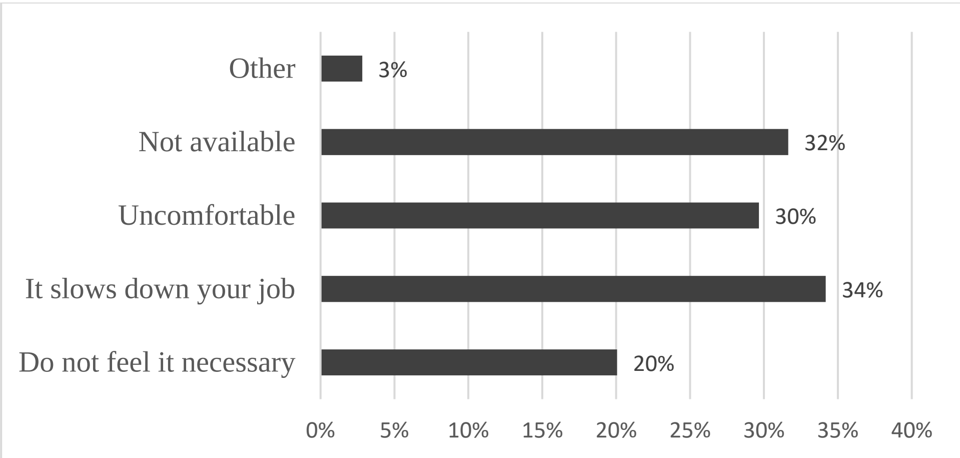


Figure 5-2 Survey results on factors that hinder PPE usage
Source (author)

- The frequency of ship visit by shore management personnel made a difference on the injury rates. The injury rate was as high as 38% when no ship visit was conducted. Sharp contrast (11%) was found compared to ships with more than two visit per year.
- The injury rate was 13% when maintenance routines were (very) well executed but was as high as 20% otherwise.

- Constant feedback and sharing of lessons from previous accident create awareness, which in turn reduced the occupational injury risks. The injury rate was around 10% when the company always share the learnt lessons but was 32% if otherwise.

5.3.3 Injury characteristics

The following discoveries were made about the injury characteristics after a closer examination of the injury records.

- 56% of the injuries happened after 3 months on board; 30% occurred between the 1^{st} and 3^{rd} month on board; and only 14% happened within the 1^{st} month on board.
- 82% of the injuries happened at sea while only 18% happened at port.
- 60% of the injuries were associated with slip, trips and fall, making up the biggest group. 5% were associated with fall from height. Cut of fingers accounted for 9%. The remaining 26% were attributed to other causes, including burn, sprain, and so on.
- As to the part of body that got injured, 62% caused harm to the crew's limbs. 25% of the injuries were in the head and 15% were related with the torso.
- 66% of the injuries were minor injuries requiring first aid treatment. 12% were restricted workday case. 8% resulted in less than 3 days' loss of time, while 14% resulted more than 3 days' time loss, including cases of repatriation at the next port.
- Responses about the root causes of the injuries are shown in Figure 5-3.

The figure suggests that inexperience was found to be the number one cause for the reported injuries by respondents, followed by "Inadequate PPE". Included in the 18% of "Other" causes were "Slippery surface" "Shadow sector" "Vessel vibration" and "Lack of situational awareness".

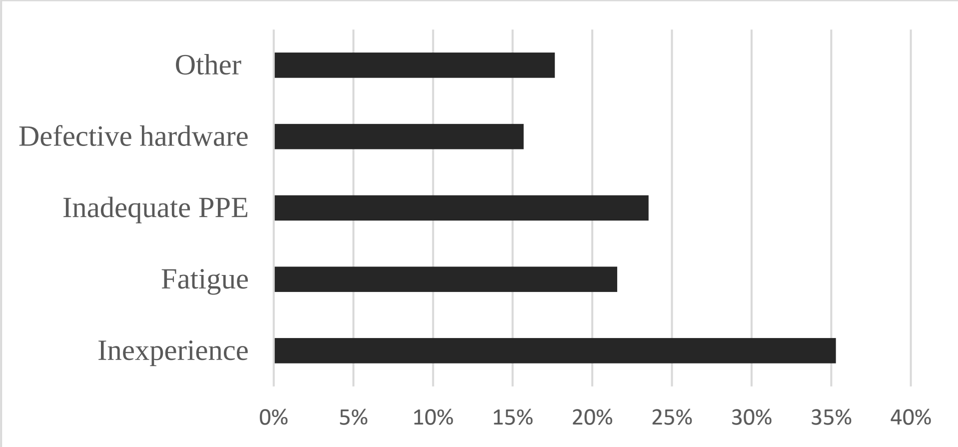


Figure 5-3 Seafarers' perceptions on the root causes of their injuries from the survey

Source (author)

5.4 Injury risk modelling based on BN

5.4.1 Variable reduction: Chi-square test

As mentioned above, the final questionnaire contained 28 questions, corresponding to more than twenty influencing factors. To reduce the number of variables, a preliminary filtration was conducted before proceeding to further analyses with the chi-square tests between the risk factors and the target variable "Injury" to check whether there is significant relationship between the influencing factors and the seafarer's injury record. Two-way contingency tables were built for the target variable "Injury" and any other variables, as the basis for the p-value calculation.

Chi-square tests were performed for a preliminary filtration of variables. Since Chi-square test works better when the expected frequencies are fairly large, the initial categories of the factors were combined to form larger groups (Frankfort-Nachmias & Leon-Guerrero, 2010; Michael, 2001). All variables became binary variables after the combination. The combinations were also made considering the injury rates i.e. categories of similar injury rate were combined. For instance, for experience groups, the injury rates for "<2 Years" "2-5 Years" and "6-10 Years" were almost the same and those of "11-20 Years" and ">20

Years” were similar. Therefore, the former three groups were combined into a larger group of “<=10 Years” while the latter formed the group “>10 Years”. The variable “Position” was reclassified into “Rank” and “Department”. P-values from the chi-square tests for the combined variables are shown in Table 5-2.

Normally, a p-value smaller than 0.05 is considered significant to reject the null hypotheses. In the present analysis, variables with a p-value of greater than 0.05 but smaller 0.2 were also kept for further analysis (Olaf C Jensen et al., 2004). Based on this criterion, the following variables were excluded in this initial step, including “Rank” “Duty duration” “New ship” “Familiarity” “Job Risk assessment” “Procedure design” “Defective equipment/hardware” and “PPE usage”.

Table 5-5 P-values from the Chi-square test

Variable	Age	Experience	Department	Rank	Duty duration	New ship
P-value	0.044	0.010	0.094	0.729	0.366	0.343
Variable	Familiarity	Adequate training	Rest hours	Job risk awareness	Job Risk assessment	Risk communication
P-value	0.981	0.196	0.190	0.198	0.316	0.043
Variable	Procedure design	Shortcut	House keeping	Defective equipment/hardware		
P-value	0.413	0.060	0.223	0.505		
Variable	PPE unavailability	PPE training	PPE usage	Shore visit	Maintenance	Accident feedback
P-value	0.000	0.033	0.386	0.096	0.078	0.000

Consistent with many other studies, “Age” and “Sea experience” of seafarers were found to be important risk factors. As to the relationship between position and injury, department was identified as a significant influential factor while rank was not, which is different with the findings in (Olaf Chresten Jensen, JFL Sørensen, et al., 2004). On the other hand, even though "PPE usage" was considered as one important factor, the evidence was not strong enough to support this. Instead, "PPE unavailability" was found to be of great importance. This might be due to the fact that humans tend to be less frank about their own safety behaviour and many people chose "Always" when asked about the frequency of PPE usage. PPE training was shown to be an influential factor. However, since only 4% of the surveyed population reported not having proper PPE training, this variable was also excluded for both association rule analysis and BN analysis. Consistent with (HSE, 2002), timely accident investigation and feedback was proved to be significant for influencing injury rate.

5.4.2 Association rule analysis

5.4.2.1 Discoveries from the

In addition, the mining of association rules was also performed among the reduced variables to discover the inter-relationships between different variables. The discovered inter-relationship were used to provide knowledge for the BN structure construction.

Association rules analysis was originally proposed for the market analysis. It can be used to discover the associations among attributes in a big database and making conclusion about casualty, constraints and dependency (Jiang & Cai, 2013). The three most important measures for association rules are "Support", "Confidence" and "Lift".

The support of A to B measures the frequency of a transaction that contains both A and B.

$$\text{support}(A \rightarrow B) = P(A \cup B) \tag{5-1}$$

The confidence of A to B means the percentage of a transaction containing A that also contains B.

$$\text{confidence}(A \rightarrow B) = P(B|A) = P(A \cup B)/P(A) \tag{5-2}$$

The lift of A to B is the ratio between the confidence of the rule and the expected confidence of the rule. It measures whether the rule in the target is much better than in the total population. A rule is considered useful if its lift value is greater than one.

$$\text{lift}(A \rightarrow B) = \text{confidence}(A \rightarrow B)/P(B) = P(A \cup B)/(P(A)P(B)) \quad (5\text{-}3)$$

A is called the antecedent or Left Hand Side (LHS) of the rule, while B is called the consequent or Right Hand Side (RHS) of the rule. Normally, a threshold is set for minimum support and minimum confidence. In this study, the minimum support and minimum confidence were set as 0.3 and 0.9.

The most popular algorithm for computing association rules is the APRIORI algorithm, which discovers association rules in two steps, ①finding out the most frequent item set that satisfies the minimum support, and ②producing the rules that satisfy the minimum confidence. More details of the algorithm can be found in (Agrawal & Srikant, 1994). In applications, the obtained rules that satisfy the minimum support and confidence may still be redundant. In fact, if a rule is a super rule of another rule, and the lift for the former rule is the same or smaller, then the former rule is considered redundant (Zhao, 2015). For example, the rule 'A, B, C→D' is redundant to the rule 'A, B→D', since it does not contain extra information. More generally, in a collection of rules $R=R_1, R_2 \cdots R_n$, R_j is redundant if there exists R_i that is more general than R_j (Zaki, 2000). The association rules package "arules" in R was used for analysis in this study, and the rules obtained in the first step were further pruned using the method reported in (Zhao, 2015) to remove redundancy.

5.4.2.2 Discoveries from the association rule analysis

The minimum support and minimum confidence were set as 0.3 and 0.9 respectively. Under this setting, 1,405 rules were produced. However, after further pruning the redundancy (see Section 2.3), the number reduced to 75. Figure 5-4 shows the grouped association rules.

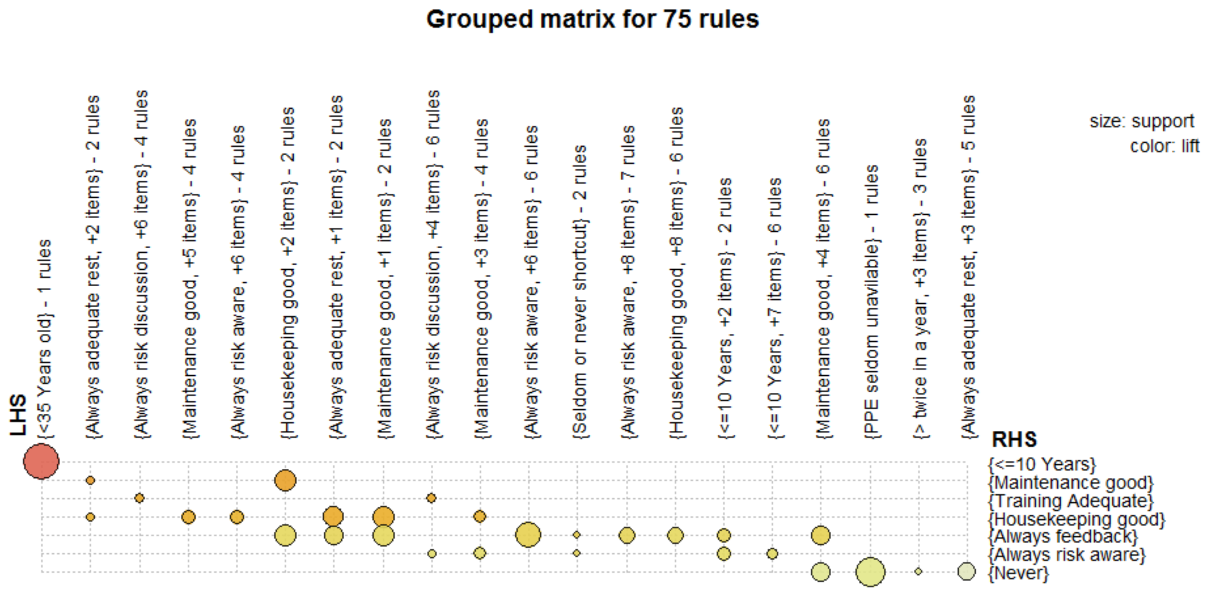


Figure 5-4 Grouped association rules

Source (author)

The rules where RHS is "Injury=Never" are listed in Table 5-6. The interpretation of these rules is in the form of "if …then…".

Table 5-6 Sample association rules where RHS is "Injury=Never"

Conditions (LHS)	Inference (RHS)	Support	Confidence	Lift
PPE seldom unavailable	Never injured	0.579	0.911	1.064
Always feedback, Deck	Never injured	0.520	0.902	1.054
Always adequate rest, Always feedback	Never injured	0.506	0.904	1.056
Always adequate rest, Training Adequate	Never injured	0.460	0.901	1.052
Deck, Good maintenance	Never injured	0.452	0.909	1.062
Always adequate rest, Always risk discussion	Never injured	0.429	0.905	1.057
Always risk discussion, Deck	Never injured	0.410	0.901	1.052
Always adequate rest, Deck	Never injured	0.395	0.903	1.055
> twice in a year, Always feedback	Never injured	0.364	0.908	1.061
> twice in a year, Maintenance good	Never injured	0.331	0.907	1.060
> twice in a year, Always risk discussion	Never injured	0.314	0.910	1.063
>=35 Years old	Never injured	0.311	0.909	1.062

For example, the first rule in Table 5-6 could be interpreted as "if PPE is seldom unavailable on a ship, then the seafarer on this ship would be expected to have zero injuries during his tour of duty", which was supported by 57.9% of the cases with a confidence of 91.1%. These rules provided guidance for building the BN model structure in the next section.

5.4.3 BN model for the injury probability predictions

5.4.3.1 BN structure of the injury prediction model

Based on the causal relations of "Direct causes", "Indirect causes" and "Root causes", an initial tree-structured BN topology was built with prior knowledge both from the literature and the association rules. The parameters were then learnt using the survey data. Adjustments were made to the structure until it passed the validation tests, as will be discussed in section 5.4. In total, nine major risk factors were included in the final model. Figure 5-5 shows the model with the marginal probabilities. One distinct advantage of BN is its capability of explanation. In addition, the values of all the individual variables in the BN model can be observed, while the traditional regression models only produce gross output variables.

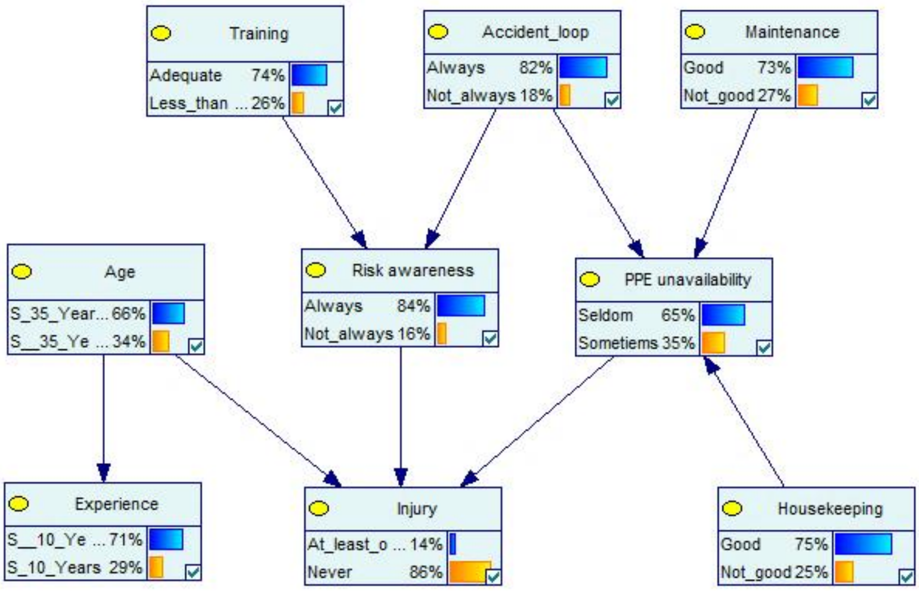


Figure 5-5 The BN model for probabilistic prediction of seafarers' injuries

Source (author)

5.4.3.2 Inferences using the BN model for injury analysis

The variables of direct influence were “Age”, “Risk awareness” and “PPE unavailability”. “Age>=35 years old”, “Always having risk awareness” and “PPE seldom unavailable” had homogeneous tendency of decreasing injury rate. The level of influence by these three variables is shown in Table 5-7:

Table 5-7 Effects of the three direct influencing factors on the injury probabilities

Nodes	Age		Risk awareness		PPE unavailability	
States	<35 Years old	>=35 Years old	Not always	Always	Sometimes or always	Seldom
Posterior injury probability	0.170	0.093	0.199	0.132	0.238	0.091
Absolute changes	0.027	-0.077	0.106	-0.067	0.106	-0.147
Relative changes	19%	-54%	74%	-47%	74%	-103%

The influences of these three factors were quite significant, with the minimum reduction effect of 47%. “PPE unavailability” had the biggest potential to decrease the injury probability. “Age” and “Sea Experience” were highly correlated, as revealed in the association rules analysis. If “Age<35” was observed for a seafarer, it was almost certain (98%) that he had less than 10 years of sea experience. The “Risk awareness” could be enhanced through “Training” and “Accident feedback loop”. Overall, 26% of the respondents felt that they did not receive adequate training for their job. Meanwhile, 18% of the respondents reported that their company did not share the accident lessons frequently among the crew. When both percentages were set to 100%, the chances of always having risk awareness was only 48%. However, when both percentages changed to 0%, implying adequate training and good accident feedback loop, then the chance of always having “risk awareness” would be increased to 89%.

The maximum changes in the injury probability given the observations of all other variables' true state were examined using function 5-1.

$$\Delta P_{I_Y} = \max P(Injury = At\ least\ once \mid Y = Y_j) - \min P(Injury = At\ least\ once \mid Y = Y_i) - \\ = \max P(Injury = Never \mid Y = Y_i) - \min P(Injury = Never \mid Y = Y_j) \tag{5-4}$$

where Y_j and Y_i are the two states which produce the largest and smallest values for the probability of having at least one injury. For binary variables, Y_j and Y_i are the two states of the variables respectively. The results are summarised in Table 5-8.

Table 5-8 Changes in injury probability given observations on other variables' true state

Variables	State 1	Max	State 2	Min	Difference
PPE unavailability	Sometimes or always	0.238	Seldom	0.091	0.147
Age	<35 Years old	0.170	>=35 Years old	0.093	0.077
Experience	<=10 Years	0.163	>10 Years	0.096	0.067
Risk awareness	Not always	0.199	Always	0.132	0.066
Accident loop	Not always	0.173	Always	0.137	0.036
Maintenance	Not good	0.165	Good	0.135	0.030
Housekeeping	Not good	0.163	Good	0.137	0.027
Training	Less than adequate	0.147	Adequate	0.142	0.005

The variables in Table 5-8 were arranged in descending order according to the maximum difference. In addition to the three direct influencing factors, "Experience" also produced large maximum difference. "PPE unavailability" produced the largest difference among all variables, implying that PPE availability was the most influential factor. Meanwhile, the younger seafarers below 35 years or with less than 10 years' experience would be the next risk prone group to focus on.

Figure 3 shows the backward inference if an injury is observed.

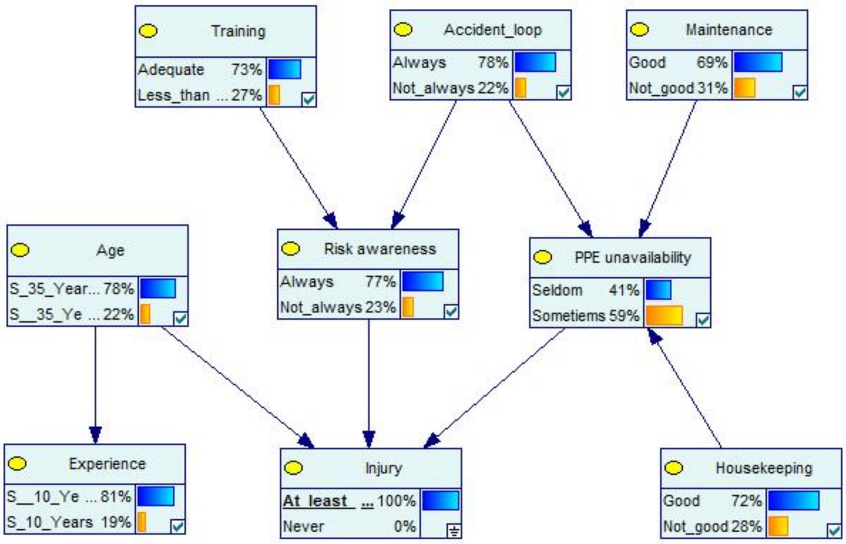


Figure 5-6 Posterior probabilities for all nodes with observed injury

Source (author)

The biggest change of posterior probability also occurred for the variable “PPE unavailability” with “PPE unavailability=Sometimes” changing from 0.35 to 0.59. Thus, when an injury occurred, without any other evidence, we could infer that PPE unavailability was very likely (59%) to be the cause.

5.5 Model validation

5.5.1 Qualitative validations of the model

As mentioned in Subsection 3.1.4, in order to get a validated BN model, it is necessary to ensure confidence in the model structure, the discretisation, the parameterisation and the model behaviour. The parameterization confidence and the behaviour confidence for the present model could be validated through quantitative tests, as will be discuss in Subsection 5.4.2. Here the confidence in the model structure regarding the number of nodes included, the states of nodes, their discretisation, as well as the links between nodes will be discussed.

First, all nodes were identified potential risk factors from the literature review, as shown in Subsection 5.1, even though they were not meant to be exhaustive. The factors are appropriate for the study of occupational injuries. One factor intentionally excluded for study is the “nationality” of the seafarers, due to the limitation of the scale of the survey, and also considering the fact that “nationality” exerts its influence through other factors. All nodes were binary nodes, combined from the states of the initially categories, which were compact sets and covered the full ranges of all possible states. For example, the three levels, “Always” “Sometimes” and “Seldom or never” covered all possible frequencies for many safety practices. The node “Age” and “Experience” were discretized based on (Bailey et al., 2010). The binarization was based on the contingency table with respect to the relative risk levels.

The links between nodes were constructed based on the knowledge summarized from the literatures as well as from the discoveries of association rules. Since the quantitative part also depends very much on the structure definition, the structure was modified a few times until all validation tests were satisfied.

5.5.2 Quantitative validations of the model

In this Subsection, four quantitative validation tests were performed, i.e. comparisons of marginal probabilities from the learnt model and the raw statistics from the survey data, conduction of the two types of sensitivity analyses, and the axiom test (K. Li et al., 2010; Zhang, Yan, Yang, Wall, & Wang, 2013).

5.5.2.1 Comparison of the marginal probabilities in the model with the raw data

The comparison between the marginal probabilities learnt from the BN model and the raw survey statistics is shown in Table 5-9. The last column shows the absolute difference, which was typically small, implying that the results were consistent.

Table 5-9 Comparison of marginal probabilities for all nodes from the BN model and the raw data statistics

Nodes	States1	Marginal	Survey data	States2	Marginal	Survey data	Absolute difference
Age	<35 Years old	0.658	0.658	>=35 Years old	0.342	0.342	0.000
Experience	<=10 Years	0.712	0.712	>10 Years	0.288	0.288	0.000
Training	Adequate	0.740	0.740	Less than adequate	0.260	0.260	0.000
Risk awareness	Always	0.837	0.828	Not always	0.163	0.172	0.009
Housekeeping	Good	0.754	0.754	Not good	0.246	0.246	0.000
PPE unavailability	Seldom	0.646	0.636	Sometime or always	0.354	0.364	0.011
Maintenance	Good	0.729	0.729	Not good	0.271	0.271	0.000
Accident loop	Always	0.816	0.816	Not always	0.184	0.184	0.000
Injury	At least once	0.143	0.144	Never	0.857	0.856	0.001

5.5.2.2 Sensitivity to findings

The entropy value for the node "Injury" was found to be 0.178. The mutual information between "Injury" and all other variables was calculated and presented in Table 5-10.

Table 5-10 Mutual information between "Injury" and all other nodes

Y	I(Injury, Y)
PPE availability	8.08E-03
Experience	3.64E-03
Age	2.40E-03
Risk awareness	1.37E-03
Accident loop	3.82E-04
Maintenance	3.00E-04
Housekeeping	2.21E-04
Training	1.06E-05

Here, “PPE unavailability” proved to be the most informative variable. Contrasting with Table 5-8, “Experience” was found to be more informative than “Age”. The rankings of other variables are all consistent with the findings in Table5-8.

5.5.2.3 Sensitivity to parameters

There is more than one sensitivity value for each node, corresponding to each parameter/conditional probability number. The maximum sensitivity values for all variables in the present BN model are summarized in Table 5-11.

Table 5-11 Maximum sensitivity values for all nodes in the BN model for injury

Nodes	Maximum sensitivity values
Injury	3.59E-01
Age	7.55E-02
PPE availability	6.48E-02
Experience	0*
Risk awareness	3.57E-02
Accident loop	3.89E-02
Maintenance	2.97E-02
Housekeeping	2.64E-02
Training	5.60E-03

It can be seen from Table 5-11 that the model is not sensitive to most parameters except for the CPT of the node “Injury”, which had the largest sensitivity value of 0.359. The second and third largest values were for the node “Age” and “PPE unavailability” respectively, both of which were below 0.1. For a closer examination, the learnt conditional probabilities for the node “Injury” are presented in Table 5-12.

Theoretically, the maximum and minimum conditional probability value should be the probability when all the three parent factors take the worst or best state. This could be verified in Table 5-12. All other conditional probabilities in Table 5-12 were also reasonable except for the value with asterisk (7.8E-04), which needed modification.

However, since the sensitivity value for this parameter was very small (0.04), the modification of this parameter will not affect the results considerably.

Table 5-12 Conditional probabilities for the node "Injury"

Age	<35 Years Old				>=35 Years Old			
Risk awareness	Always		Not always		Always		Not always	
PPE unavailability	Seldom	Sometime	Seldom	Sometime	Seldom	Sometime	Seldom	Sometime
At least once	0.102	0.254	0.200	0.316	0.048	0.167	7.8E-04*	0.286
Never	0.898	0.746	0.800	0.684	0.952	0.833	0.999	0.714

5.5.2.4 Axiom test

Another validation test used for this study is the axiom test (Goerlandt & Montewka, 2014) (Zhang et al., 2013). The axiom states that the total influence of probability variations of *x* parameters (towards homogeneous tendency) should be no smaller than the one from y (y∈x) parameters. This axiom is observed by the current model, as demonstrated by the results shown in Table 5-13.

Table 5-13 Axiom test for the node "Injury"

Condition (e)	P(Injury=at least once|e)	Change	Condition(e)	P(Injury=at least once|e)	Change
Age: <35 Years	0.172	+19.9%	Age: >=35 Years	0.077	-46.6%
Age: <35 Years, Risk awareness: Not always	0.233	+62.6%	Age: >=35 Years, Risk awareness: Always	0.061	-57.1%
Age: <35 Years; Risk awareness: Not always; PPE unavailability: Sometime or always	0.286	+99.4%	Age: >=35 Years; Risk awareness: Always; PPE unavailability: Seldom	0.037	-74.2%

CHAPTER 6 Conclusions and future research

6.1 Summary and contributions of the research

Risk analysis provides a systematic, scientific approach to describe the maritime transportation system which provides support decision making on project designs, policy development, and resources allocation (Szwed & Van Dorp, 2002). The quantitative risk assessment for maritime accidents modelling is a critical component for safety management. However, data availability has always been the biggest challenge in the risk modelling practice, even though many risk assessment techniques have been developed and applied for safety related problems. This is the case particularly for accident probability modelling, since accident consequences could be modelled through engineering methods under specific scenarios in a more deterministic manner. This thesis mainly investigates the probabilistic modelling of maritime accidents using the advanced BN method, with a focus on where and how to obtain data and utilize them in the models, both for the LP-HC accidents and HP-LC accidents, considering the inherent differences of these two accidents types. The following summarize the contributions of the current research in both academic and non-academic side.

6.1.1 BN modelling for the LP-HC accidents: the case of ship collisions

6.1.1.1 Academic contributions

(1) Comprehensive knowledge on the risk assessment models for ship collisions

Ship collision was chosen for the case study for its strategic importance, dominant prevalence and potential catastrophic consequence to human lives, economic losses and environmental damages. A systematic literature review was carried out in Section 2.1 about the existing quantitative risk assessment methods for ship collisions. The characteristics and scope of applications of various models, especially the detailed models for estimation of geometrical and causation probabilities, were discussed as well, providing a holistic view on the quantitative risk analysis on ship collisions. Detailed geometrical collision probability models were found to be necessary for the risk mapping of a specific geographic area, while detailed models of causation probability were needed for the evaluation of countermeasures for effective accident management and preventions. The comprehensive knowledge provides a solid basis for interested researchers to gain a quick and clear understanding of the risk assessment models on ship collisions.

(2) Comprehensive knowledge on expert elicitations techniques for BN parameterization

Due to the scarcities of historical statistics for rare accidents, knowledge elicitation from the industry experts has been the main source for the parameterization of BN models for the LP-HC accidents. An extensive review was also conducted regarding the challenges on the knowledge elicitation from domain experts in BN applications, with a focus on the ways to reduce the elicitation workload and the selection of elicitation techniques for individual probability elicitation. Meanwhile, applications of the elicitation techniques in previous maritime risk assessment models were summarized. The review provided insights into the practices for general BN applications as well as knowledge on the status for BN modelling in the maritime domain. Probability scale configured with both numerical numbers and qualitative statements was identified to be an advantageous method for fast and distinct elicitation of a large number of conditional probabilities. The linguistic terms were found close to the natural language and corresponded to the human cognitive process.

(3) An innovative method to deal with epistemic uncertainties using BN with interval probabilities

It is a big challenge for the experts to assign precise conditional probabilities for BN models. Meanwhile, the exact probability numbers provided by the experts often carry a high level of epistemic uncertainty due to the lack or incompleteness of human knowledge, since the experts are often not asked about their own expertise but about others' failure rates during the elicitation process (Brooker, 2011). The application of a special type of credal network, i.e. BN extension with interval probabilities, was explored in this study, which enabled the quantitative representation of the epistemic uncertainty. This is the one of the few research that addressed the epistemic uncertainty in maritime risk assessment and the only one that quantitatively represented epistemic uncertainty with interval numbers as far as we are aware, which adds more values to BN and its practical applications in this field.

The elicited interval probabilities were directly processed with the GL2U method, which was extended from the exact updating algorithm 2U for the polytree structured binary BN with extra binarization and loopy steps. The only approximation in the GL2U method was brought by the loopy step. Since multiple experts (11 in the case of this study) were involved in the elicitation process, a weighted average method was developed to combine the interval probabilities from all experts. The novel combination method was adapted from Hu et al. (2012) by incorporating the concept of distance between interval probabilities but differed by attaching weights to each interval rather than to each expert. It overcame the drawbacks of other combination methods by generating the weights objectively from the obtained interval probabilities without any extra elicitation steps.

Interval marginal probabilities were obtained from the GL2U method with the combined interval conditional probability parameters. The levels of ambiguity and uncertainty were reflected in the width of the intervals. For example, the probability interval for the node "Detection=Yes" was quite narrow, ranging from 0.966 to 0.999, indicating relatively low uncertainty in the detection probability. Nevertheless, the interval marginal probability for the node "Collision=Yes" was [0.359, 0.886], ranged from "Medium likelihood" to "Likely". The interval marginal probabilities obtained from the GL2U method contained the point marginal probabilities computed from the traditional BN, which indicated consistency between the two methods (BN could be regarded as a special case of CN). The interval parameters specified by each expert were also used for calculations. Different levels of discrepancies were found among the result, which verified the existence of uncertainties associated with experts' judgment and strengthen the necessity for dealing with this issue.

6.1.1.2 Managerial implications

(1) Predictive tool for prevention of collisions

The probabilistic BN model built in Chapter 4 provides an advanced tool for ship collision accident management and prevention. The causal relations for ship collisions were explicitly reflected in the model with probability numbers to quantify the links between the causal factors. Suggestions about potential RCOs could be easily made with the model. Besides, the risk reduction effects of the suggested RCO could be assessed by calculating the scenario occurrence probabilities, due to the predictive capacity of the BN model. Alternatively, it is also possible to assess other RCOs proposed by the management team by integrating the RCO into the BN model without affecting the original model since BN is such a flexible method. The model can also be further extended to a decision support software. No pre-knowledge about complicated probability theory is required for the potential user. Instead, only observations about the states of the causal factors, i.e. nodes in the model are desirable for applications. Therefore, it is a user friendly predictive tool for implementation in shipping/ship management companies, insurance companies as well as other stakeholders.

(2) Risk informed decision making

Decision-making with RCOs bears the most significant practical value for effective risk mitigation and management. However, the cost and benefit analysis is extremely difficult in applications, subjected to various sources of uncertainty from the risk analysis results as well as the type of cost and benefit items to include, the interest rate to apply and the monetization of the tangible and intangible values. The subjective evaluation method adapted from (Y. F. Wang et al., 2013) was more practical by using the relative preference levels instead of the exact cost and benefits values. Meanwhile, the interval probabilities enabled the explicit representation of epistemic uncertainties, thus making it possible for the user to make risk informed decision making. The effects of the uncertainties in risk assessment result on the decision-making process were illustrated via a simplified example. The ranking of RCOs was observed to change significantly when the risk reduction values were calculated with changes in the upper and lower probability bounds of the interval probabilities compared to the traditional BN.

6.1.2 BN modelling for the HP-LC accidents: the case of seafarers' workplace injuries

6.1.2.1 Academic contributions

(1) Theoretical framework for studies of occupational accidents and injuries

The literature review provided a comprehensive theoretical framework for understanding the occupational accidents and injuries, both in the maritime and other sectors. A number of potential risk factors were summarized, revealing knowledge on the direct causes, indirect causes and root causes for the workplace accidents and injuries. Four streams of studies were identified: ①qualitative analysis through literature studies, field interviews and so on, ②simple quantitative analysis with descriptive statistics, using percentage number or indexes such as incident/odd ratios, ③quantitative classification of the historical accident or injury records with advanced data mining techniques such as ANN, CART, etc., and ④quantification of experts' opinions through AHP, Fuzzy methods, reliability methods as well as BN. The existing studies on seafarers' job related accidents or injuries fall into the first two categories, which only allowed for single or a few variables to be studied with predetermined linear relationships.

(2) Advanced risk model using BN approach with empirical data

Methodology wise, this is the first BN application to study the seafarers' workplace injuries so far as we are aware. As to data sources, unlike the LP-HC accidents, the modelling of HP-LC accidents does not necessarily rely on experts' opinions in most cases, since more empirical data can be obtained due to its higher frequency. The extensive survey carried out in this study allowed the collection of first hand empirical data from the industry. The carefully designed survey questionnaire covered a wide range of potential risk factors identified from the literature. Respondents were asked about their normal practices regarding these risk factors, as well as the number of injuries they encountered during the latest tour of duty. The survey data overcame the drawbacks of data from historical injury database or from the insurance claim records, by capturing both accident cases and the ordinary cases. Thus, the prediction of injury probability as well as the verification the influence of potential risk factors was possible. The empirical survey data also overcame the uncertainties with the experts' judgements.

6.1.2.2 Managerial implications

(1) Predictive tool to support management of seafarer injuries

The management of HP-LC accidents is as important as that of the LP-HC accidents due to their prevalence, while the latter is more threatening for the associated catastrophic consequences. As a stereotype of the HP-LC accidents, seafarers' injury incidents have been very common aboard commercial ships. Improving the job safety and reducing the occupational injuries are not only of great importance to the seafarers themselves, but also brings direct benefits to shipping companies by saving the loss of working time, expenditures on worker compensation insurance premiums as well as liabilities and legal costs. The probability concept of BN made it possible for the seafarers' injury accident to be predicted in a probabilistic rather than deterministic way. As with the BN model for collisions, the injury model also allows the evaluation of the potential effects of management campaigns before implementation for its ability to be updated with new evidences on individual or combination of risk factors.

(2) Knowledge discoveries from the empirical survey

An overall injury rate of 14.4% was observed for the respondents during their latest tour of duty, based on the self-reporting data from the survey. The data summary from the survey provided a general overview on the injury patterns as well as the risk prone groups. Significance of the risk factors was tested using the χ^2 tests, based on which eight factors i.e. "Rank", "Tour duration", "Change of ship", "Familiarity", "Job Risk assessment", "Procedure design", "Defective equipment/hardware" and "PPE usage" were filtered out in the first place. The remaining factors were retained as co-variables for further analysis with association rules and BN. Analysis with association rules revealed the interrelationships among the remaining variables, which provided guidance in developing the BN model topology. The final validated BN model contained nine major risk factors, including "PPE unavailability", "Age", "Experience", "Risk awareness", "Accident loop", "Maintenance", "Housekeeping" and "Training". The most influencing factors were identified to be "Availability of PPE", "Age", "Experience" and "Risk awareness" of seafarers from the model analysis, indicating that improvement on these aspects should be set as the top priority by the shipping companies in order to reduce the injury rates in the future. The exact level of changes in the injury rate after implementation of individual or combination of risk measures were obtained from inferences as well.

6.2 Recommendation for applications

Involvement of the senior management team in the shipping and ship management companies is the key for bringing practical value to the risk assessment framework described in this study. The knowledge from domain experts is always important data sources for the BN model construction and parameterization in the maritime context. The support from the management team is also critical for successful data collection of any form. The execution power of senior management team grants access to databases and documentations from various channels within the company, such as the incident and near miss reports as well as the internal and external audits. However, the training of the management team about the BN theory is essential. The sophisticated theoretical knowledge should be communicated to the industry experts in an easy and explicit way.

In applications, risk assessment could start with the demand for the evaluation of safety campaigns or policies proposed by the company, or with the need for suggestions on potential campaign or policy alternatives. It is important to note that obtaining a risk value or a probability number should never be the objective of any risk analysis. Instead, it is the interpretation of the risk value or the probability number that matters. Changes of the simulated risk values before and after implementation of the potential risk countermeasures are useful information for decision making. The risk reduction effects of two or more risk control measures are non-linear and should could be evaluated carefully using the risk model. The absolute cost and benefit values are necessary to decide whether it is economically beneficial to adopt a risk control measure. However, considering the difficulty in obtaining these absolute values and the associated uncertainty, obtaining the ranking of the RCOs is as important.

6.3 Limitations and future research diresctions

6.3.1 BN modelling for the LP-HC accidents: the case of ship collisions

6.3.1.1 Improvement on probability elicitation method

Two versions of probability elicitation tools were developed in the present study: the trial version of a java based elicitation tool which enabled the user to specify the upper and lower bounds for interval conditional probabilities by simply dragging the two sliders; and the excel-based tool which allowed the rapid elicitation by choosing the proper linguistic terms from a drop-down list. The latter was adopted in the actual elicitation process for the collision model, as described in Chapter 4. The final interval conditional probabilities were obtained from the conversion of the directly elicited linguistic terms, according to the pre-established definitions. However, despite the convenience and relative ease enabled by the excel elicitation tool, it restricted the flexibility for representing different levels of uncertainty, since the linguistic terms are associated with pre-determined interval probability. Some of the interval posterior probabilities were exaggerated due to the large width of the linguistic terms. Improvement should be made to the elicitation tool in the future, so as to achieve a better balance between efficiency and flexibility.

6.3.1.2 Decision making considering uncertainty

The example in Section 4.4 illustrated how uncertainty in the risk assessment result could affect the ranking of potential RCOs in the cost and benefit analysis. Two special cases were analysed for risk reduction calculation with the interval posterior probabilities, i.e. the changes of lower and upper probability bound separately. These two special cases were only representatives among many other possible cases, since the true posterior probabilities could vary independently within the intervals. Therefore, the true risk reduction number contained so much uncertainty and were thus difficult to estimate. The example only showed how the uncertainty in risk analysis result impact the decision-making process. However, which number to adopt for risk reduction calculation should be studied in future research. In fact, decision making with interval probabilities itself is an area well worth research, where many methods, such as the simulation method, the linear analytical method and the maximum entropy method, have been proposed for analyses. Future research could be strengthened in this direction to improve the decision making with interval probabilities.

6.3.2 BN modelling for the HP-LC accidents: the case of seafarers' workplace injuries

6.3.2.1 Sample size

Data collection was one of the most critical but challenging process in this study. First, it was not easy to reach out to the potential respondents, even though many channels both online and offline were explored for the data collection. For seafarers who were on duty aboard ships, access to internet was a big constraint. Moreover, they were busy with many tasks as well as various paper work and internal/external surveys, which discouraged participation. In contrast, the seafarers on vacation enjoyed more free time, yet reaching out to them and involving them was again not easy. Fortunately, owing to the help from many contacts, a total of 354 responses were collected. However, this sample size is still limited, considering the properties of BN and the number of risk factors covered in the study, since BN is a method widely known for its high demand for data in modelling. As mentioned in the methodology, the number of conditional probabilities for each node in a BN model is $i \times n^k$. Therefore, to improve the reliability of the learnt parameters, the injury BN model included only nine major risk factors, all of which were binarized nodes after the combination of original states. Had larger sample size been obtained, the binarization step could have been avoided. Meanwhile, structural learning could have been possible given more data.

6.3.2.2 Hybrid BN structure definition method

The parameters of the present BN model were learnt from the survey data, while the model structure was built with pre-knowledge. In fact, knowledge discoveries from pure data or from a combination of data and human knowledge are also possible. The learning or hybrid learning BN methodology to incorporate expert elicited structural priors into the structure learning from data is of great practical value. The hybrid BN, in particular, can overcome the inefficiency caused by the demand for time, knowledge and data by the individual method alone. Meanwhile, different types of prior knowledge could be integrated in the modelling, depending on the confidence of the expert's knowledge, from full structure elicitation to direct causal connections and correlations elicitation. One of the future research directions is to enhance the confidence in the BN structural specification by applying the structure learning algorithms or the hybrid learning methodology. This, however, also depends on the improvement in sample size as mentioned above.

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APPENDIX A ORIGINAL ELICITATION RESULT

Table A1 The original elicited CPTs from all experts for the node “Collision”

Manoeuvre of ship 1	Manoeuvre of ship 2	Collision=Yes										
		1	2	3	4	5	6	7	8	9	10	11
Correct	Correct	Extremely unlikely	Very likely	Extremely unlikely	Very unlikely	Very unlikely	Very unlikely	Extremely unlikely	Very unlikely	Very unlikely	Very unlikely	Extremely unlikely
	Incorrect	Very unlikely	Very likely	Medium likelihood	Likely	Medium likelihood	Very likely	Medium likelihood	Medium likelihood	Medium likelihood	Likely	Medium likelihood
Incorrect	Correct	Very unlikely	Very likely	Medium likelihood	Likely	Medium likelihood	Very likely	Medium likelihood	Medium likelihood	Medium likelihood	Likely	Medium likelihood
	Incorrect	Likely	Very likely	Likely	Likely	Very likely	Very unlikely	Virtually certain	Very likely	Very likely	Very likely	Very likely

Table A2 The original elicited CPTs from all experts for the node “Manoeuvring”

Manoeuvre planning	Steering failure	Competence of the OOW	Navigational complexity	Manoeuvring=Correct										
				1	2	3	4	5	6	7	8	9	10	11
Correct	Yes	High	High	Unlikely	Unlikely	Extremely unlikely	Medium likelihood	Likely	Likely	Likely	Medium likelihood	Medium likelihood	Likely	Medium likelihood
			Low	Very likely	Unlikely	Extremely unlikely	Unlikely	Very likely	Unlikely	Very likely	Likely	Very likely	Likely	Likely
		Low	High	Extremely unlikely	Very unlikely	Extremely unlikely	Very likely	Extremely unlikely	Virtually certain	Unlikely	Very unlikely	Unlikely	Medium likelihood	Very unlikely
			Low	Unlikely	Very unlikely	Extremely unlikely	Very likely	Medium likelihood	Very likely	Unlikely	Very unlikely	Medium likelihood	Unlikely	Unlikely
	No	High	High	Very likely	Virtually certain	Likely	Very unlikely	Very likely	Very unlikely	Very likely	Very likely	Very likely	Very likely	Very likely
			Low	Virtually certain	Virtually certain	Very likely	Extremely unlikely	Virtually certain	Extremely unlikely	Virtually certain	Very likely	Virtually certain	Virtually certain	Virtually certain

		Low	High	Medium likelihood	Very unlikely	Unlikely	Likely	Likely	Medium likelihood	Very unlikely	Unlikely	Medium likelihood	Very unlikely	Unlikely
			Low	Likely	Very unlikely	Medium likelihood	Medium likelihood	Very likely	Unlikely	Unlikely	Medium likelihood	Likely	Likely	Medium likelihood

Table A3 The original elicited CPTs from all experts for the node "Manoeuvre planning"

Detection	Navigational complexity	Competence of the OOW	Communication between ships	Manoeuvre planning=Correct										
				1	2	3	4	5	6	7	8	9	10	11
Yes	High	High	Yes	Virtually certain	Very likely	Very likely	Very likely	Very likely	Virtually certain	Very likely	Likely	Virtually certain	Likely	Very likely
			No	Very likely	Very likely	Likely	Very likely	Likely	Virtually certain	Very unlikely	Medium likelihood	Very likely	Unlikely	Likely
		Low	Yes	Medium likelihood	Unlikely	Likely	Medium likelihood	Medium likelihood	Very unlikely	Medium likelihood	Medium likelihood	Very likely	Likely	Unlikely
			No	Unlikely	Unlikely	Medium likelihood	Unlikely	Unlikely	Very unlikely	Extremely unlikely	Unlikely	Likely	Very unlikely	Very unlikely
	Low	High	Yes	Virtually certain	Very likely	Very likely	Virtually certain	Virtually certain	Virtually certain	Virtually certain	Very likely	Virtually certain	Very likely	Virtually certain
			No	Virtually certain	Very likely	Likely	Virtually certain	Very likely	Virtually certain	Medium likelihood	Very likely	Virtually certain	Likely	Very likely
		Low	Yes	Likely	Unlikely	Likely	Likely	Very likely	Very unlikely	Medium likelihood	Medium likelihood	Very likely	Medium likelihood	Medium likelihood
			No	Medium likelihood	Unlikely	Medium likelihood	Medium likelihood	Likely	Very unlikely	Extremely unlikely	Medium likelihood	Very likely	Unlikely	Unlikely

Table A4 The original elicited CPTs from all experts for the node "Navigational System Detection"

Updating routine	Navigational system signal	Navigational system detection=Yes										
		1	2	3	4	5	6	7	8	9	10	11
Followed	Good	Virtually certain	Very likely	Very likely	Very likely	Virtually certain	Virtually certain	Very likely	Very likely	Virtually certain	Very likely	Virtually certain
	Bad	Unlikely	Very unlikely	Unlikely	Likely	Likely	Very likely	Very unlikely	Likely	Very likely	Likely	Very unlikely
Not followed	Good	Very unlikely	Very unlikely	Unlikely	Very likely	Very likely	Very unlikely	Extremely unlikely	Likely	Likely	Medium likelihood	Very unlikely
	Bad	Extremely unlikely	Very unlikely	Very unlikely	Likely	Very unlikely	Very unlikely	Extremely unlikely	Very unlikely	Medium likelihood	Very unlikely	Extremely unlikely

Table A5 The original elicited CPTs from all experts for the node “Visual Detection”

Visibility	Competence of the OOW	Look out person	Visual Detection=Yes										
			1	2	3	4	5	6	7	8	9	10	11
Adequate	High	Present	Virtually certain	Very likely	Very likely	Very likely	Very likely	Very likely	Virtually certain	Likely	Virtually certain	Very likely	Very likely
		Not present	Very likely	Likely	Very likely	Likely	Very likely	Likely	Unlikely	Very likely	Virtually certain	Likely	Likely
	Low	Present	Very likely	Likely	Very likely	Very likely	Very likely	Likely	Likely	Likely	Virtually certain	Likely	Likely
		Not present	Unlikely	Medium likelihood	Likely	Medium likelihood	Medium likelihood	Medium likelihood	Extremely unlikely	Medium likelihood	Very likely	Medium likelihood	Unlikely
Less than adequate	High	Present	Very likely	Likely	Medium likelihood	Very likely	Medium likelihood	Very likely	Very likely	Medium likelihood	Very likely	Likely	Likely
		Not present	Very unlikely	Likely	Medium likelihood	Medium likelihood	Medium likelihood	Likely	Extremely unlikely	Medium likelihood	Very likely	Medium likelihood	Unlikely
	Low	Present	Likely	Unlikely	Medium likelihood	Likely	Unlikely	Medium likelihood	Unlikely	Medium likelihood	Very likely	Medium likelihood	Unlikely
		Not present	Extremely unlikely	Very unlikely	Unlikely	Unlikely	Unlikely	Unlikely	Extremely unlikely	Very unlikely	Likely	Unlikely	Very unlikely

Table A6 The original elicited CPTs from all experts for the node “VTS Detection”

VTS Presence	VTS Detection==Yes										
	1	2	3	4	5	6	7	8	9	10	11
Present	Very likely	Very likely	Very likely	Virtually certain	Very likely	Very likely	Very likely	Likely	Very likely	Likely	Very likely
Not present	Very unlikely	Likely	Extremely unlikely	Very unlikely	Extremely unlikely	Extremely unlikely	Unlikely	Extremely unlikely	Extremely unlikely	Very unlikely	Extremely unlikely

Table A7 The original elicited CPTs from all experts for the node “Rest hours”

BRM	Rest hours=Adequate										
	1	2	3	4	5	6	7	8	9	10	11
Good	Virtually certain	Very likely	Very likely	Very likely	Very likely	Virtually certain	Virtually certain	Very likely	Virtually certain	Likely	Very likely
Bad	Unlikely	Unlikely	Unlikely	Very unlikely	Likely	Medium likelihood	Very unlikely	Likely	Very likely	Medium likelihood	Very unlikely

Table A8 The original elicited CPTs from all experts for the node “Fatigue”

Rest hours	Fatigue=Yes										
	1	2	3	4	5	6	7	8	9	10	11
Adequate	Very unlikely	Very unlikely	Very unlikely	Very unlikely	Very unlikely	Extremely unlikely	Very unlikely	Unlikely	Medium likelihood	Unlikely	Very unlikely
Less than adequate	Virtually certain	Very likely	Likely	Very likely	Very likely	Likely	Very likely	Likely	Very likely	Medium likelihood	Very likely

Table A9 The original elicited CPTs from all experts for the node “Distraction”

BRM	Distraction level=High										
	1	2	3	4	5	6	7	8	9	10	11
Good	Extremely unlikely	Very unlikely	Unlikely	Unlikely	Unlikely	Extremely unlikely	Likely	Unlikely	Likely	Unlikely	Very unlikely
Bad	Very likely	Likely	Likely	Very likely	Very likely	Likely	Very unlikely	Likely	Very likely	Likely	Very likely

Table A10 The original elicited CPTs from all experts for the node “Updating routine”

Safety culture	Updating routine=Followed										
	1	2	3	4	5	6	7	8	9	10	11
Good	Virtually certain	Virtually certain	Likely	Very likely	Very likely	Virtually certain	Very likely	Very likely	Virtually certain	Likely	Very likely
Bad	Very unlikely	Very unlikely	Unlikely	Very unlikely	Medium likelihood	Unlikely	Very unlikely	Unlikely	Likely	Unlikely	Unlikely

Table A11 The original elicited CPTs from all experts for the node “Competence of OOW”

Crew training	Fatigue	Distraction level	Competence of OOW= High										
			1	2	3	4	5	6	7	8	9	10	11
Adequate	Yes	High	Unlikely	Likely	Very unlikely	Unlikely	Medium likelihood	Unlikely	Extremely unlikely	Very unlikely	Unlikely	Unlikely	Unlikely
		Low	Medium likelihood	Unlikely	Unlikely	Likely	Likely	Unlikely	Very unlikely	Unlikely	Medium likelihood	Unlikely	Medium likelihood
	No	High	Very likely	Very likely	Unlikely	Very likely	Likely	Very likely	Likely	Unlikely	Likely	Likely	Medium likelihood
		Low	Virtually	Very	Medium	Very	Very	Virtually	Virtually	Very	Very	Very	Very

			certain	likely	likelihood	likely	likely	certain	certain	likely	likely	likely	likely
Less than adequate	Yes	High	Extremely unlikely	Extremely unlikely	Very unlikely	Very unlikely	Very unlikely	Extremely unlikely	Extremely unlikely	Very unlikely	Very unlikely	Very unlikely	Extremely unlikely
		Low	Very unlikely	Unlikely	Unlikely	Likely	Unlikely	Extremely unlikely	Extremely unlikely	Unlikely	Unlikely	Medium likelihood	Very unlikely
	No	High	Unlikely	Unlikely	Unlikely	Likely	Medium likelihood	Unlikely	Medium likelihood	Unlikely	Medium likelihood	Unlikely	Unlikely
		Low	Likely	Unlikely	Medium likelihood	Medium likelihood	Likely	Unlikely	Likely	Medium likelihood	Likely	Medium likelihood	Medium likelihood

Table A12 The original elicited CPTs from all experts for the node “Maintenance routine”

safety culture	Maintenance routine=Followed										
	1	2	3	4	5	6	7	8	9	10	11
Good	Very likely	Very likely	Likely	Very likely	Very likely	Virtually certain	Very likely	Very likely	Virtually certain	Likely	Very likely
Bad	Extremely unlikely	Very unlikely	Unlikely	Unlikely	Likely	Very unlikely	Medium likelihood	Unlikely	Very unlikely	Unlikely	Very unlikely

Table A13 The original elicited CPTs from all experts for the node “BRM”

safety culture	BRM=Good										
	1	2	3	4	5	6	7	8	9	10	11
Good	Virtually certain	Very likely	Likely	Very likely	Likely	Virtually certain	Very likely	Very likely	Very likely	Likely	Very likely
Bad	Extremely unlikely	Very unlikely	Unlikely	Medium likelihood	Medium likelihood	Unlikely	Very unlikely	Unlikely	Medium likelihood	Unlikely	Very unlikely

Table A14 The original elicited CPTs from all experts for the node "Training"

safety culture	Training=Adequate										
	1	2	3	4	5	6	7	8	9	10	11
Good	Very likely	Very likely	Very likely	Very likely	Very likely	Virtually certain	Very likely	Likely	Likely	Likely	Very likely
Bad	Extremely unlikely	Very unlikely	Unlikely	Medium likelihood	Likely	Unlikely	Very unlikely	Unlikely	Unlikely	Unlikely	Very unlikely

Table A15 The original elicited CPTs from all experts for the node "Look out"

Visibility	BRM	Look out person=Present										
		1	2	3	4	5	6	7	8	9	10	11
Adequate	Good	Virtually certain	Very likely	Unlikely	Very likely	Very likely	Extremely unlikely	Very likely	Unlikely	Extremely unlikely	Unlikely	Very likely
	Bad	Very unlikely	Very unlikely	Very unlikely	Unlikely	Very unlikely	Extremely unlikely	Unlikely	Very unlikely	Extremely unlikely	Unlikely	Very unlikely
Less than adequate	Good	Virtually certain	Very likely	Very likely	Virtually certain	Virtually certain	Virtually certain	Very likely	Very likely	Virtually certain	Very likely	Virtually certain
	Bad	Very unlikely	Very unlikely	Very unlikely	Unlikely	Medium likelihood	Medium likelihood	Unlikely	Very likely	Likely	Likely	Medium likelihood

Table A16 The original elicited CPTs from all experts for the node "Visibility"

Time of the day	Weather	Visibility=Good										
		1	2	3	4	5	6	7	8	9	10	11
Daytime	Good	Virtually certain	Very likely	Very likely	Virtually certain	Very likely	Very likely	Very likely	Very likely	Virtually certain	Likely	Virtually certain
	Bad	Medium likelihood	Very unlikely	Unlikely	Medium likelihood	Medium likelihood	Medium likelihood	Very unlikely	Unlikely	Unlikely	Unlikely	Medium likelihood
Night	Good	Virtually certain	Likely	Likely	Very likely	Very likely	Medium likelihood	Very likely	Likely	Likely	Medium likelihood	Likely
	Bad	Medium likelihood	Very unlikely	Very unlikely	Very unlikely	Unlikely	Extremely unlikely	Very unlikely	Unlikely	Extremely unlikely	Very unlikely	Extremely unlikely

Table A17 The original elicited CPTs from all experts for the node "Steering failure"

Maintenance routine	Steering failure=Yes										
	1	2	3	4	5	6	7	8	9	10	11
Followed	Extremely unlikely	Unlikely	Unlikely	Very unlikely	Very unlikely	Very unlikely	Very unlikely	Unlikely	Extremely unlikely	Unlikely	Very unlikely
Not followed	Virtually certain	Very likely	Likely	Very likely	Medium likelihood	Likely	Very likely	Medium likelihood	Medium likelihood	Likely	Medium likelihood

Table A18 The original elicited CPTs from all experts for the node “Navigational signal”

Weather	Navigational system settings	Size of encounter ship	Navigational system signal=Good										
			1	2	3	4	5	6	7	8	9	10	11
Good	Correct	Big ships	Virtually certain	Very likely	Very likely	Virtually certain	Very likely	Virtually certain	Very likely	Very likely	Virtually certain	Virtually certain	Very likely
		Small vessels	Likely	Likely	Likely	Virtually certain	Very likely	Very likely	Likely	Likely	Likely	Likely	Likely
	Incorrect	Big ships	Unlikely	Very unlikely	Very unlikely	Virtually certain	Likely	Very likely	Unlikely	Very likely	Likely	Likely	Unlikely
		Small vessels	Very unlikely	Extremely unlikely	Very unlikely	Medium likelihood	Medium likelihood	Very unlikely	Very unlikely	Medium likelihood	Unlikely	Medium likelihood	Very unlikely
Bad	Correct	Big ships	Very likely	Likely	Likely	Virtually certain	Very likely	Virtually certain	Very likely	Very likely	Very likely	Medium likelihood	Likely
		Small vessels	Medium likelihood	Medium likelihood	Medium likelihood	Medium likelihood	Likely	Medium likelihood	Very unlikely	Medium likelihood	Likely	Unlikely	Medium likelihood
	Incorrect	Big ships	Very unlikely	Very unlikely	Very unlikely	Very likely	Likely	Likely	Medium likelihood	Likely	Medium likelihood	Unlikely	Very unlikely
		Small vessels	Extremely unlikely	Extremely unlikely	Very unlikely	Very unlikely	Unlikely	Extremely unlikely	Extremely unlikely	Very unlikely	Extremely unlikely	Extremely unlikely	Extremely unlikely

Table A19 The original elicited CPTs from all experts for the node “Navigational system settings”

Competence of OOW	Navigational system settings=Correct										
	1	2	3	4	5	6	7	8	9	10	11
High	Very likely	Very likely	Very likely	Virtually certain	Very likely	Virtually certain	Virtually certain	Very likely	Very likely	Likely	Very likely
Low	Extremely unlikely	Unlikely	Unlikely	Unlikely	Unlikely	Unlikely	Very unlikely	Unlikely	Medium likelihood	Unlikely	Very unlikely

APPENDIX B COMBINED INTERVAL PROBABILIES FROM ALL EXPERTS

Table B1 The combined interval conditional probabilities for the node "Collision"

Manoeuvre of ship 1	Manoeuvre of ship 2	Collision=Yes	
		Lower bound	Upper bound
Correct	Correct	0.018	0.079
	Incorrect	0.434	0.714
Incorrect	Correct	0.434	0.714
	Incorrect	0.832	0.952

Table B2 The combined interval conditional probabilities for the node "Manoeuvring"

Manoeuvre planning	Steering failure	Competence of the OOW	Navigational complexity	Manoeuvring=Correct	
				Lower bound	Upper bound
Correct	Yes	High	High	0.394	0.664
			Low	0.595	0.762
		Low	High	0.125	0.233
			Low	0.192	0.384
	No	High	High	0.839	0.933
			Low	0.921	0.947
		Low	High	0.212	0.438
			Low	0.399	0.663

Table B3 The combined interval conditional probabilities for the node "Manoeuvre planning"

Detection	Navigational complexity	Competence of the OOW	Communication between ships	Manoeuvre planning=Correct	
				Lower bound	Upper bound
Yes	High	High	Yes	0.903	0.986
			No	0.714	0.871
		Low	Yes	0.357	0.635
			No	0.098	0.281
	Low	High	Yes	0.968	0.998
			No	0.890	0.974
		Low	Yes	0.480	0.731
			No	0.264	0.509

Table B4 The combined interval conditional probabilities for the node “Navigational system detection”

Updating routine	Navigational system signal	Navigational system detection=Yes	
		Lower bound	Upper bound
Followed	Good	0.937	0.994
	Bad	0.445	0.624
Not followed	Good	0.275	0.420
	Bad	0.032	0.112

Table B5 The combined interval conditional probabilities for the node “Visual detection”

Visibility	Competence of the OOW	Look out person	Visual detection=Yes	
			Lower bound	Upper bound
Adequate	High	Present	0.911	0.990
		Not present	0.761	0.927
	Low	Present	0.760	0.936
		Not present	0.327	0.615
Less than adequate	High	Present	0.719	0.901
		Not present	0.357	0.623
	Low	Present	0.327	0.598
		Not present	0.073	0.229

Table B6 The combined interval conditional probabilities for the node “VTS detection”

VTS Presence	VTS detection=Yes	
	Lower bound	Upper bound
Present	0.891	0.985
Not present	0.019	0.068

Table B7 The combined interval conditional probabilities for the node “Rest hours”

BRM	Rest hours=Adequate	
	Lower bound	Upper bound
Good	0.922	0.991
Bad	0.246	0.454

Table B8 The combined interval conditional probabilities for the node “Fatigue”

Rest hours	Fatigue=Yes	
	Lower bound	Upper bound
Adequate	0.027	0.133
Less than adequate	0.837	0.961

Table B9 The combined interval conditional probabilities for the node “Distraction”

BRM	Level of distraction= High	
	Lower bound	Upper bound
Good	0.111	0.281
Bad	0.759	0.925

Table B10 The combined interval conditional probabilities for “Updating routine”

Safety culture	Updating routine=Followed	
	Lower bound	Upper bound
Good	0.914	0.987
Bad	0.097	0.284

Table B11 The combined interval conditional probabilities for “OOW Competence”

Crew training	Fatigue	Distraction level	Competent OOW=High	
			Lower bound	Upper bound
Adequate	Yes	High	0.108	0.310
		Low	0.220	0.471
	No	High	0.676	0.865
		Low	0.911	0.987
Less than adequate	Yes	High	0.006	0.063
		Low	0.099	0.277
	No	High	0.165	0.416
		Low	0.408	0.699

Table B12 The combined interval conditional probabilities for "Maintenance routine"

safety culture	Maintenance routine=Followed	
	Lower bound	Upper bound
Good	0.895	0.985
Bad	0.086	0.248

Table B13 The combined interval conditional probabilities for the node "BRM"

Safety culture	BRM= Good	
	Lower bound	Upper bound
Good	0.877	0.978
Bad	0.112	0.308

Table B14 The combined interval conditional probabilities for the node "Training"

Safety culture	Training=Adequate	
	Lower bound	Upper bound
Good	0.872	0.978
Bad	0.098	0.281

Table B15 The combined interval conditional probabilities for the node "Look out"

Visibility	BRM	Look out person=Present	
		Lower bound	Upper bound
Adequate	Good	0.580	0.689
	Bad	0.022	0.122
Less than adequate	Good	0.953	0.996
	Bad	0.286	0.509

Table B16 The combined interval conditional probabilities for the node "Visibility"

Time of the day	Weather	Visibility=Good	
		Lower bound	Upper bound
Daytime	Good	0.922	0.991
	Bad	0.193	0.451
Night	Good	0.711	0.906
	Bad	0.027	0.119

Table B17 The combined interval conditional probabilities for “Steering failure”

Maintenance routine	Steering failure=Yes	
	Lower bound	Upper bound
Followed	0.034	0.151
Not followed	0.644	0.855

Table B18 The combined interval conditional probabilities for “Navigational system signal”

Weather	Navigational system settings	Size of encounter ship	Navigational system signal=Good	
			Lower bound	Upper bound
Good	Correct	Big ships	0.937	0.994
		Small vessels	0.692	0.911
	Incorrect	Big ships	0.475	0.646
		Small vessels	0.109	0.275
Bad	Correct	Big ships	0.842	0.961
		Small vessels	0.340	0.649
	Incorrect	Big ships	0.316	0.511
		Small vessels	0.004	0.037

Table B19 The combined interval conditional probabilities for the node “Navigational system settings”

Competence of OOW	Navigational system settings=Correct	
	Lower bound	Upper bound
High	0.911	0.990
Low	0.092	0.299

APPENDIX C QUESTIONNAIRE FOR THE SURVERY ON SEAFARERS' INJURIES

Survey on the effects of individual/organizational/situational factors

on occupational injuries on ships

Thank you for spending your precious time filling this questionnaire. Please be assured about the confidentiality of the survey.

- **The survey is totally anonymous.**
- **All the information we collect here is purely for research purpose.**
- **Our analysis will be based on collective/group basis rather than on individual basis.**
- **We will not disclose your answers to anyone else.**

There are five parts in the questionnaire. Part 1 is about Demographic information; Part 2 covers Personal factors; Part 3 asks about Workplace condition; Part 4 refers to Management and supervision and Part 5 collects information about injuries you suffered during your latest duty.

Please answer all questions based on your latest duty.

Part 1 Demographic information
1. What is your gender? ☐Female ☐Male 2. What is your age? (Years old) ☐<25 ☐25-34 ☐35-44 ☐45-55 ☐>55 3. How long is your sea service (Years)? ☐<2 ☐2-5 ☐6-10 ☐11-20 ☐>20 4. What is your nationality? ______________ 5. What type of ship are you working on for your latest duty? ☐Tanker ☐Container ship ☐Bulk carrier ☐General cargo ☐Passenger ship ☐Other___________ 6. What is your position on your ship? ☐Senior deck Officer ☐Senior engine Officer ☐Catering ☐Junior deck officer ☐Junior engine Officer ☐Deck ratings ☐Engine ratings 7. How long have you been in your current position (rank)? ______________ 8. How long is the duration of your latest contract? ☐<=6 months ☐7-12 months ☐>12 months
Part 2 Personal factors
9. Have you ever worked on this ship or her sister ship before?

☐Yes ☐No

10. How familiar are you with the operation of equipment related to your job on this ship?
☐Very unfamiliar ☐Unfamiliar ☐Moderate ☐Familiar ☐Very familiar

11. Do you agree with the statement: The current on-the-job training provided by my organization is adequate to meet the changing needs of workplace.
☐Strongly disagree ☐Disagree ☐Neutral ☐Agree ☐ Strongly agree

12. Can you get a minimum of 10 hours' rest in any 24-hour period and 77 hours in any 7-day period?
☐ Always ☐Sometimes ☐Seldom

13. Normally, do you feel difficult to concentrate on your job due to
Repetitive tasks ☐ Yes ☐No
Isolated surroundings ☐ Yes ☐No
Ship vibration/noise etc. ☐ Yes ☐No
Work pressure ☐ Yes ☐No
Fatigue ☐ Yes ☐No

14. Are you aware of potential risks related to the tasks you are doing?
☐ Yes, always ☐Yes, sometimes ☐No, seldom

15. Do you conduct job risk analysis before performing the tasks?
☐ Yes, for all tasks ☐ Only for non-routine tasks ☐No, seldom

16. Is the result of job risk analysis discussed among all staff related to the tasks?
☐ Yes, always ☐Yes, sometimes ☐No, seldom

17. Do you agree that the working procedures are relevant and easy to comply?
☐Strongly disagree ☐Disagree ☐Neutral ☐Agree ☐ Strongly agree

18. Do you take alternative methods or shortcuts to get work done?
☐ Always ☐Sometimes ☐Seldom or never

Part 3 Workplace condition

19. How is the housekeeping condition (e.g. cleaning, storage and alike) on your ship?
☐Very bad ☐Bad ☐Moderate ☐Good ☐ Very good

20. Are there cases you have to carry out your task with defective tools/equipment/materials?
☐ Always ☐Sometimes ☐Seldom

21. Have you ever found difficulty in getting proper personal protection equipment (PPE) on your ship?
☐ Always ☐Sometimes ☐Seldom

22. Did you get training on the proper ways to use PPEs?
☐ Yes ☐No

23. How often do you use PPE when performing your job?
☐ Always ☐Sometimes ☐Seldom

24. What might be the reason you do not use PPE for some occasions?
    ☐ Do not feel it necessary ☐It slows down your job ☐Uncomfortable
    ☐Not available ☐Other___________

Part 4 Management and supervision

25. How often do the company shore management personnel visit your ship?
    ☐ No visit ☐Once in a year ☐Twice in a year ☐More than twice in a year

26. How is the execution of PMS (planned maintenance systems) on your ship?
    ☐Very bad ☐Bad ☐Moderate ☐Good ☐ Very good

27. Does your company investigate into accidents/incidents and share the lessons with you and other crew?
    ☐ Always ☐Sometimes ☐Seldom

Part 5 Injuries during the latest duty

28. Have you suffered any injuries during your latest duty?
    ☐Never ☐Once ☐Twice ☐More than twice

    Details about the injury if any

Injury 1	Injury 2	Injury 3
When did it happen? ☐1st month on board ☐1st -3rd months on board ☐3rd months onwards	When did it happen? ☐1st month on board ☐1st -3rd months on board ☐3rd months onwards	When did it happen? ☐1st month on board ☐1st -3rd months on board ☐3rd months onwards
Where did it happen? ☐At sea ☐At port	Where did it happen? ☐At sea ☐At port	Where did it happen? ☐At sea ☐At port
How did you get injured? ☐Slip, trip and Fall ☐Fall from height ☐Cut of Fingers ☐Other_________	How did you get injured? ☐Slip, trip and Fall ☐Fall from height ☐Cut of Fingers ☐Other_________	How did you get injured? ☐Slip, trip and Fall ☐Fall from height ☐Cut of Fingers ☐Other_________
Which part of your body was injured? ☐Head ☐Neck ☐Torso ☐Limbs	Which part of your body was injured? ☐Head ☐Neck ☐Torso ☐Limbs	Which part of your body was injured? ☐Head ☐Neck ☐Torso ☐Limbs
How severe was it? ☐First Aid Case ☐Restricted workday case ☐<=3 days loss time injury ☐>3 days loss time injury	How severe was it? ☐First Aid Case ☐Restricted workday case ☐<=3 days loss time injury ☐>3 days loss time injury	How severe was it? ☐First Aid Case ☐Restricted workday case ☐<=3 days loss time injury ☐>3 days loss time injury
What was the root cause? ☐Inexperience ☐Fatigue ☐Inadequate PPE ☐Defective hardware ☐Other________________	What was the root cause? ☐Inexperience ☐Fatigue ☐ Inadequate PPE ☐Defective hardware ☐Other________________	What was the root cause? ☐Inexperience ☐Fatigue ☐ Inadequate PPE ☐Defective hardware ☐Other________________

❖ **Thank you again for your participation**

APPENDIX D CONDITIONAL PROBABILITY TABLE OF THE BN MODEL FOR INJURY PROBABILITY PREDICTION

Table D1 The CPT for the node "Injury"

Age	<35_Years				>=35_Years			
Risk awareness	Always		Not always		Always		Not always	
PPE unavailability	Seldom	Sometime	Seldom	Sometime	Seldom	Sometime	Seldom	Sometime
At_least_once	0.102	0.254	0.200	0.316	0.048	0.167	0.001	0.286
Never	0.898	0.746	0.800	0.684	0.952	0.833	0.999	0.714

Table D2 The CPT for the node "Risk awareness"

Accident loop	Always		Not always	
Training	Adequate	Less than adequate	Adequate	Less than adequate
Always	0.887	0.847	0.719	0.485
Not always	0.113	0.153	0.281	0.515

Table D3 The CPT for the node "PPE availability"

Accident loop	Always				Not always			
Maintenance	Good		Not good		Good		Not good	
Housekeeping	Good	Not good	Good	Not good	Good	Not good	Good	Not good
Seldom	0.757	0.609	0.577	0.471	0.727	0.286	0.308	0.087
Sometimes	0.243	0.391	0.423	0.529	0.273	0.714	0.692	0.913

Table D4 The CPT for the node "Experience"

Age	<35_Years_old	>=35_Years_old
<=10_Years	0.983	0.190
>10_Years	0.017	0.810

APPENDIX E PUBLICATIONS ARISING FROM THE THESIS

Journal papers

- **Zhang, G.**, & Thai, V. V. (2016). Expert elicitation and Bayesian Network modelling for shipping accidents: A literature review. Safety Science, 87, 53-62.

- **Zhang, G.**, & Thai, V. V. Inferences with Interval Probabilities in Bayesian Belief Network for Maritime Accident Modelling. (Safety Science, under review)

- **Zhang, G.**, & Thai, V. V., Law, A. Quantitative risk assessment of seafarers' non-fatal injuries due to occupational accidents based on Bayesian Network modelling. (Risk Analysis, under review)

Conference papers

- **Zhang, G.**, & Thai, V. V. (2015). Maritime accidents risk prediction based on Bayesian Network with interval probabilities. Safety and Reliability of Complex Engineered Systems (pp. 2017-2024): CRC Press.