QUANTITATIVE RISK ASSESSMENT

FOR MARITIME SAFETY MANAGEMENT

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CERTIFICATE OF ORIGINALITY

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_______________________________ (Signed)

YIN JINGBO (Name of student)

FOR MY DEAREST PARENTS --- MR. AND MRS. YIN

FOR MY BELOVED WIFE---LIXIAN FAN

ABSTRACT

There are over 130,000 ships sailing around the world, these playing an important role in the world's economic development. However, shipping has always been characterized as a relatively risky business. With an increasing awareness of environmental protection and safety issues, research into maritime risk assessment (MRA) has become an important research domain.

In this research, the following tasks are accomplished in order to develop a quantitative risk assessment for maritime safety management.

First, this research summarizes previous studies into risk assessment by way of a literature review. It was found that the traditional and simplest way to estimate the probability of marine accidents is to consider accident statistics or expert estimation. However, both of these methods have certain limitations.

Secondly, this research is based on the safety performance of global vessels and has found various risk indicators that can be used to indicate the probability of an accident. Following this, multivariate logistic regression was used to measure the probability of the occurrence of an accident through historical data on safety indicators, such as vessel age, type, registration and classification.

Thirdly, a comprehensive database was built for this analysis. The

availability of suitable data necessary for each step of the FSA process is very important.

Fourthly, this study presents an innovative approach toward integrating logistic regression and a Bayesian Network together into risk assessment. This approach has been developed and applied to a case study in the maritime industry. It can apply to other industries as well.

Finally, a case study, which applying this risk assessment approach in the port state control program, is presented. The optimal inspection policy with regard to different vessel types, as well as the effects of changing parameters on the optimal inspection rate, is examined in the light of the risk assessment results.

PUBLICATIONS ARISING FROM THE THESIS

Journal Papers:

1. Li, K. X., Yin, J., A New Safety Index for Maritime Transportation. (Submitted).
2. Li, K. X., Yin, J., Yang, Z., Wang, J., Bayesian Network with Quantitative Input for Maritime Risk Analysis. (Submitted).
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Conference Papers:

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6. Li, K. X., Yin, J., Yang, Z., Wang, J., The effect of shipowners' effort in vessels accident: a Bayesian Network Approach. The Fourth International Forum on Shipping, Ports and Airports (IFSPA) 2010. Department of Logistics & Maritime Studies. October 15-18, 2010. Chengdu, Sichuan, China

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LIST OF ABBREVIATIONS

BN	Bayesian Network
FSA	Formal Safety Assessment
MoU	Memoranda of Understanding
ID	Influence Diagram
PSC	Port State Control
IMO	International Maritime Organization
CS	Classification Societies
IACS	The International Association of Classification Societies
FOC	Flags of Convenience
CPT	Conditional Probability Table
PA	Port of Authority
WCS	World Casualty Statistics
GT	Gross Tonne
ABS	American Bureau of Shipping
BV	Bureau Veritas
CCS	China Classification Society
DNV	Det Norske Veritas

GL	Germanischer Lloyd
IRS	Indian Register of Shipping
KRS	Korean Register of Shipping
LR	Lloyd's Register
NK	Nippon Kaiji Kyokai
RINA	Registro Italiano Navale
RS	Russian Maritime Register of Shipping
NE	Nash Equilibrium

Quantitative Risk Assessment for Maritime Safety Management

Chapter 1：Introduction

There are over 130,000 ships sailing around the word, this playing an important role in the world's economic development. However, shipping has always been characterized as a relatively risky business. With an increasing awareness of environmental protection and safety issues, research into maritime risk assessment (MRA) has become a major factor for marine companies when making their operating decisions, and is therefore an important research domain.

This chapter will give an overview of the MRA and introduce the background to this study. Then the objectives of this research are stated, followed by an outline of its structure.

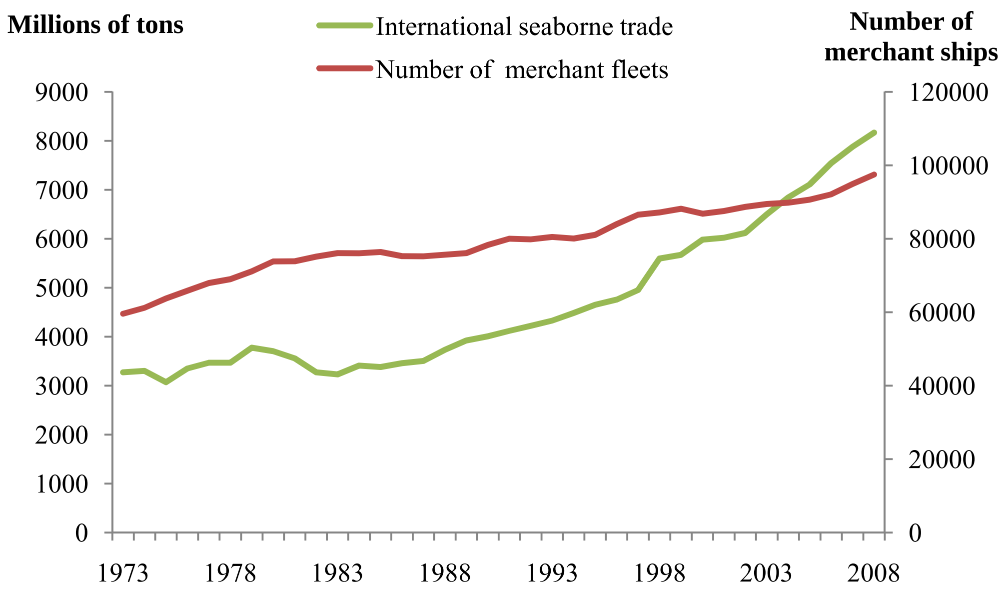
1.1 Background

With the huge increase in international trade, the demand for transportation by sea has been growing at an unprecedented rate. Figure1-1 shows that, even though affected by the global economic downturn and sharp decline in world merchandise trade in 2008, seaborne trade continued its growth. It was estimated that the 2008 international seaborne trade stood at 8.17 billion tons of goods loaded (Review of Maritime Transport, 2009).

As indicated in Figure 1-2, world seaborne trade measured in ton-miles amounted to 32,746 billion ton-miles in 2008. This represents an increase of 4.28 per cent over the last ten years, a rate higher than the growth rate for seaborne trade measured in tons.

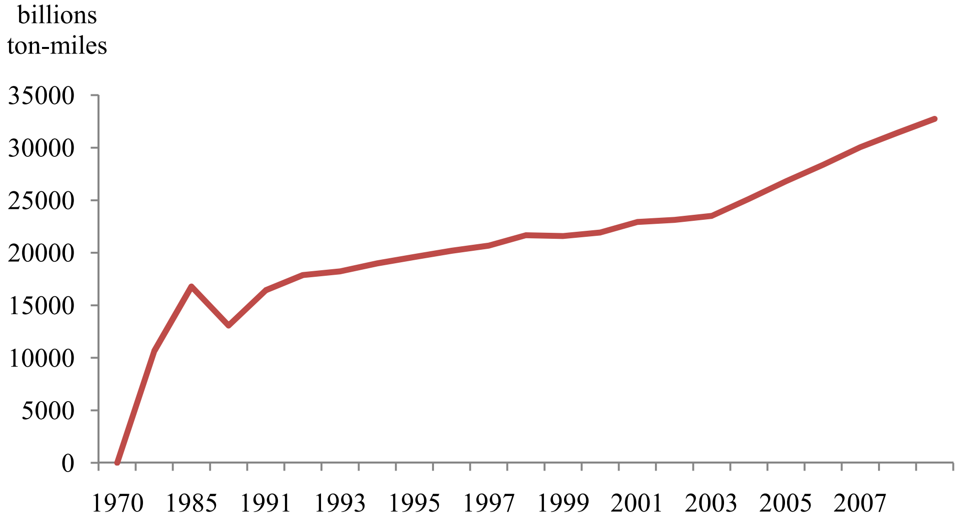
Accordingly, merchant fleets are increasing rapidly. The number of vessels increased by 67%, and total carrying capacity went up by 186% between 1973 and 2008 (Figure 1-1).

Figure 1-1: International seaborne trade and development of merchant fleets



Data Source: Review of Maritime Transport, 1960-2009

Figure 1-2: International seaborne trade in ton-miles, selected years

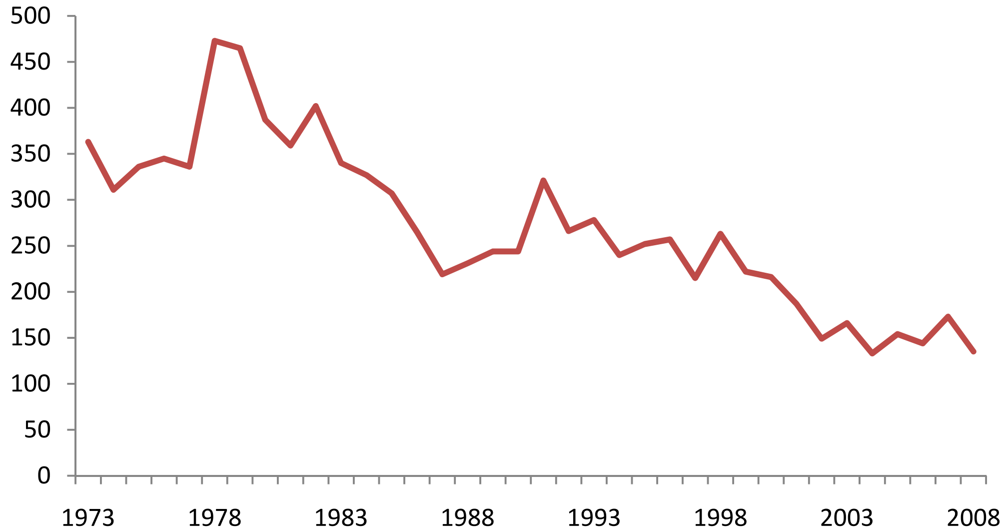


Data Source: Review of Maritime Transport, 1960-2009

However, alongside this rapid development there exist many potential threats, in particular the use of substandard ships, which can cause serious pollution and marine accidents. Examples of such accidents are easy to recollect. The grounding of the Exxon Valdez, the capsizing of the Herald of Free Enterprise and the Estonia passenger ferries accident are some of the most widely publicized accidents in maritime transportation.

So shipping today is subject to rigorous controls, and is under continuous scrutiny by both governments and the public. With the development of modern ship building technology and innovative navigation equipment, annual total losses for the world fleet have been significantly reduced, from 363 in 1973 to 135 in 2003 (Figure 1-2). It seems as though the safety record of shipping has improved, as indicated by the total loss numbers.

Figure 1-3: World merchant fleet total losses

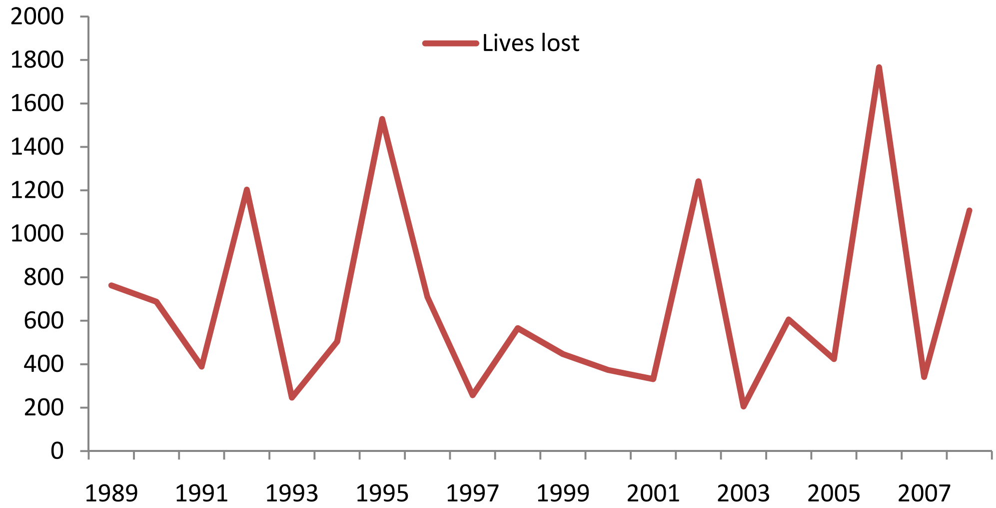


Data Source: World casualty statistics, 1993-2008

However, we still cannot state that the safety level in maritime transport is acceptable. The consequences of maritime accidents are serious, these including both large scale loss of life and severe environmental damage. The Exxon Valdez disaster cost Exxon $2.2 billion in cleanup costs alone.

Figure1-3 shows the number of lives lost from 1989 to 2008, and we do not see a decreasing trend over the last 20 years. So, for as long as ship accidents lead to fatal outcomes and the consequences for the environment are unknown, they should have our especial attention.

Figure 1-4: Lives lost in marine accidents



Data Source: World casualty statistics, 1993-2008

1.2 The risk concept

Safe: A condition in which all hazards inherent in an operation have either been eliminated or are controlled such that their associated risks are both below a tolerable threshold and reduced to a level which is as low as reasonably practicable.

Safety: Freedom from unacceptable risk or personal harm.

Maritime hazard: A perilous situation at sea that has the potential to cause injury and/or death and damage to ships, cargo and the environment.

Risk: A combination of the probability of occurrence of an undesired event and the degree of its possible consequences, or a term which combines the chance that a specified undesired event will occur and the severity of the consequences of that event (Wang and Trbojevic, 2007).

The relationship between safety and risk is that safety is used to describe the degree of freedom from danger, and the concept of risk is a way of evaluating it (Kristiansen, 2005).

Risk assessment: A comprehensive estimation of the probability and degree of the possible consequences in a hazardous situation in order to select appropriate safety measures.

Li and Cullinane (2003) follow the concept of risk in the context of engineering, and construct a maritime risk that is described by the elements of probability and severity as shown in the following formula:

$$R_i = P_i S_i$$

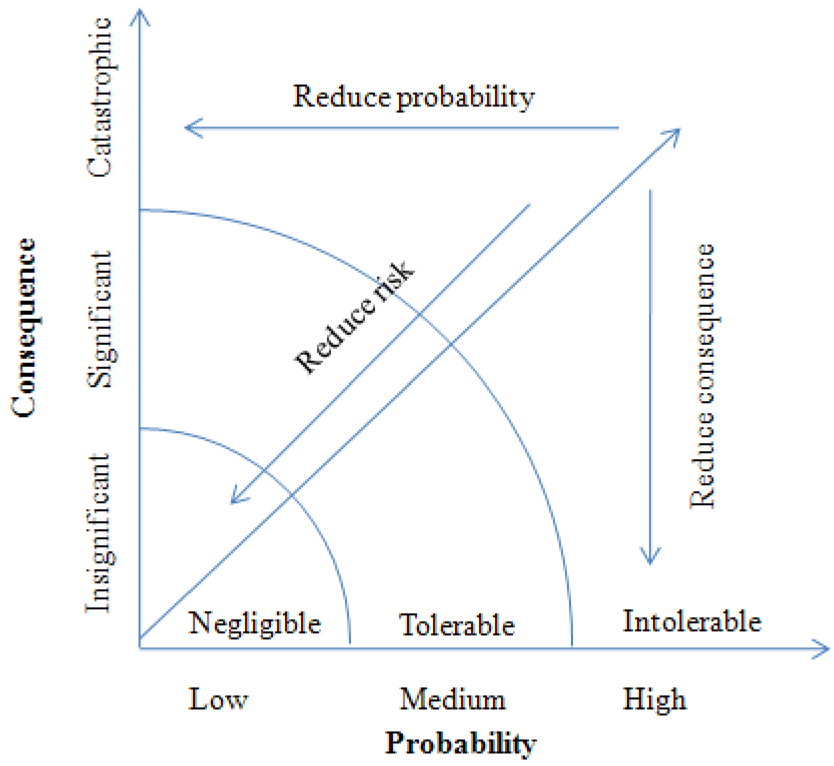
Where P_i is the probability of occurrence of a maritime accident and S_i represents the expected consequence.

Tolerability: A measure that describes the degree of acceptability of maritime risk. There are three basic tolerability levels based on the acceptability of risks: Negligible, tolerable and intolerable.

1.3 Research problems

The concept of maritime risk shows that risk has two equally important components—one is the probability and the other is the consequence. So a maritime hazard with both a high probability of occurrence and a high consequence has a high level of risk. Conversely, low level risk has a low probability and a low consequence.

Figure 1-5: Methods of reducing maritime risk



If either the consequence of the risk is insignificant or the occurrence is infrequent, then the risk level will be located in the negligible area (Figure 1-4). So there are two conceivable methods of reducing the risk level: Reduce the consequence or reduce the probability.

With the development of shipbuilding technology, more and more huge-size vessels are forming the principal part of maritime transportation. From 1973 to 2008, the number of merchant vessels increased by 67%, but the carrying capacity (GT) went up by 186% (Shipping Statistics Yearbook, 1973-2009).

Once an accident happens, then, the consequence will be more severe than before.

So the most feasible method of reducing the level of risk is to reduce the level of probability.

This leads to the first question: How can the probability of an accident be predicted?

It must be taken into account that the risk level cannot be measured directly. Traditionally, the simplest way to estimating the probability of marine accidents has been by studying accident statistics. However, statistics describe only the past—not the future. Therefore, for safety management and improvement purposes, in order to build a risk assessment indicator that examines the comparative safety levels among shipping, an evaluation mechanism for measuring the overall safety of a vessel is needed.

Secondly, how do the various factors simultaneously affect a vessel's safety level?

It is clear that accidents are the result of complex interactions within the system. Although we cannot observe the risk level directly, certain common causes often emerge as a result of casualty investigation. These factors can be seen as a predictive index for predicting a ship's safety level. The conditions affecting these factors determine the level of accident potential in a situation.

Thirdly, how can this risk assessment program be applied?

In the shipping industry, many different organizations may be involved in MRA. These include shipowners, classification societies, marine insurers, protection and indemnity clubs, ports and maritime authorities. It should therefore be evident that all these various actors within the shipping domain have different interests in MRA. So the last question is raised in order to help these different actors understand how this program can be used by diverse users.

1.4 Research objectives

The research wishes to make a contribution towards predicting the probability of accidents in the risk assessment program. The objectives of this research revolves around the following four perspectives.

The first objective is to find some indicators that can be used to indicate the probability of an accident, which based on the safety performance of global vessels. Then multivariate logistic regression is used to measure the probability of the occurrence of an accident through historical data on safety indicators, such as vessel age, type, registration and classification.

Secondly, the availability of suitable data necessary for each step of the risk assessment process is very important. Most of the time, such data is not available. Lack of reliable safety data is one of the major problems in marine safety analyses (Wang, 2001). Therefore, for this analysis, a comprehensive database needs to be established from different sources.

Thirdly, in order to analyze how all the factors simultaneously affect a vessel's safety level, a Bayesian Network (BN) model was built. This accident probability model is based on the notion of conditional probability, on the factors that determine the level of accident potential in a particular situation. The BN model can provide the probability of when a particular combination of values of the factors occurs in the system, and assess how these various factors simultaneously affect a vessel's safety level.

Fourthly, a case study applying this risk assessment program in the port state control program is needed in order to show how this risk assessment should be used. Port State Control (PSC) programs, which render port authorities able to inspect foreign ships in their own ports, have turned to such port inspections so as to prevent shipping accidents and other risks (such as safety, security, compliance with regulations, and preventive measures etc.) from occurring in their legal waters. The problems with on board inspections are: 1) Time and cost utilization is high, and 2) High risk vessels cannot be stopped prior to inspection. Hence, policies regarding port and maritime controls and inspections are calculated. The authorities require a balanced policy that assesses its economic implications and ensures rational losses, one that takes into account both the need of controls and the handling of potential accidents. The overall aim of the port authorities is to construct an optimal inspection policy combined with punishments and fines that enables maritime authorities to deploy minimum resources and achieve minimum social welfare losses, but one that also motivates shipowners to implement better safety maintenance policies.

1.5 Justification of research

The risk assessment program can be used as a safety benchmarking and management tool for different users.

Authorities can use it to pre-assess the ship before sailing to see if it is acceptable and should be granted the right to sail.

The government can use it to focus on the major safety weaknesses of individual ships in specific divisions, thus facilitating its continuing implementation of the safety oversight assessment program.

The risk assessment program can provide useful information for a shipowner to understand a ship's relative safety strengths and weaknesses in terms of manageable safety attributes, and identify functional areas for safety improvement.

The risk assessment program can also be used by insurance companies for risk and premium calculation prior to arranging an insurance policy.

Cargo owners can use this program as a reference when deciding on the transportation company and ship to use for their cargo deliveries.

1.6 Structure of thesis

The organization of this thesis is summarized as follows (Figure 1-5):

Chapter 1 is the introduction. A generic introduction about this research is first presented, and then background information provides both the motivation for the research and a discussion of certain key concepts used throughout. The research problems and its objective supply the main research aim. Following this, the structure of the thesis is presented.

Chapter 2 critically reviews the relevant literature on the theories applicable to risk assessment and maritime safety management.

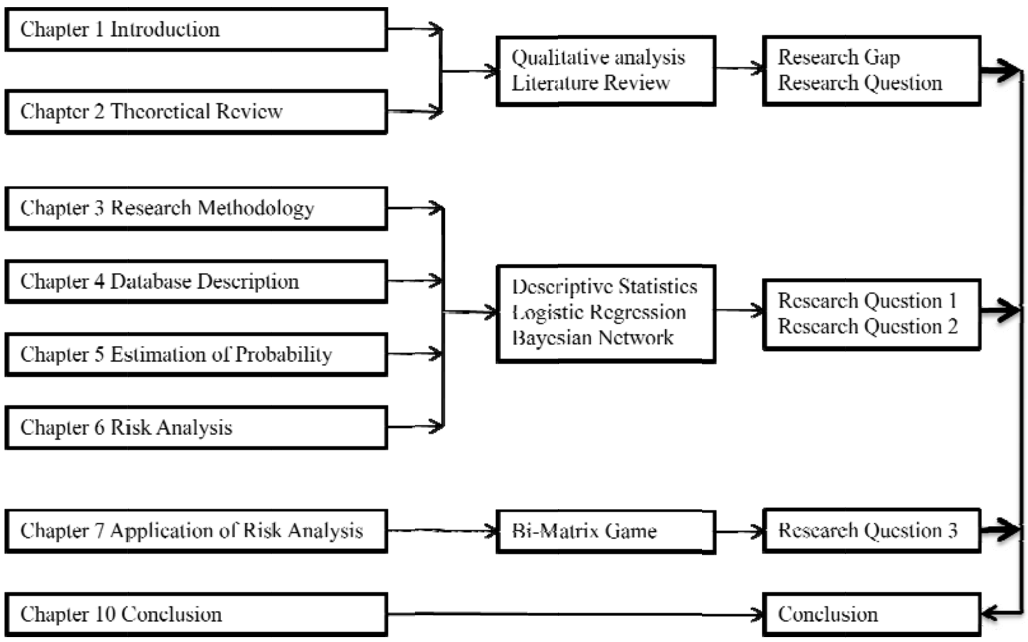
Chapter 3 provides a proposed methodology for the computation of accident probability. Then a comprehensive database used in this assessment program is described in chapter 4. Chapter 5 presents the preliminary results of the risk assessment, and binary logistic regression is used to obtain the occurrence probability of an accident for each vessel.

Chapter 6 applies a Bayesian Network (BN) approach to model the effect of different factors and their mutual influences. This approach has allowed the identification of probabilistic correlations among the basic factors of an accident.

Chapter 7 presents consecutive case studies assessing the implementation of maritime risk assessment in the port state control program, and a bi-matrix game is built between the authorities and ship operators. Then the optimal inspection rate for different vessel types and the effects of changing parameters on the optimal inspection rate is examined in light of the risk assessment results.

The last chapter, chapter 8, presents the conclusions of this research. These conclusions include comments regarding the outcomes of the research and how the initial aims and objectives are met. Some recommendations for future research are then proposed.

Figure 1-6: Thesis organization chart



Chapter 2：Literature Review

Critical reviews of theories about risk assessment, maritime safety management and different approaches to quantifying the risks in maritime transportation are presented in this chapter. This literature review will provide the research's contextual background and find any gaps in previous research.

2.1 Maritime risks

"Shipping is perhaps the most international of all the world's great industries and is one of the most dangerous." (International Maritime Organization, 2010)

Its unique environment and characteristics lay down many challenges in connection with safety management, which should be arranged in order to keep sufficient control of all safety aspects and to be prepared for all foreseeable situations that could possibly cause an accident. In order to manage safety in a proper way, the safety manager needs sufficient information to support the process of decision-making.

However, safety is a complex concept, and at the same time is not an easily observed and directly measurable state. Dynamics, its international nature, latent errors, and human and organizational errors are some features having a bearing on safety. So observing safety is difficult.

Maritime risk and safety are linked both conceptually and practically (Hollnagel, 2008). Maritime safety can be described as the degree at which the maritime risks are at an acceptable level (Kristiansen, 2005). The pragmatic link between the two concepts is that safety is usually measured by the number of specified unwanted events, such as accidents and incidents (Hollnagel, 2008). This means that a higher level of safety is equivalent to a lower level of risk.

In order to have the risks under control, the risks involved must be assessed, and effective risk control options to deal with the most significant risks must be developed and put into operation. Therefore, indirect measurements of safety levels, risk assessments, are required.

The main objectives of risk assessment are usually to prevent unwanted events, such as occupational accidents. The use of risk assessment techniques in major hazard industries has grown significantly over recent years (DNV, 2001). Such industries comprise nuclear power production, offshore industries and the various modes of transport, which have a typical feature is that they have an inherent potential to cause large losses. The harm caused by maritime accidents can include injury to personnel (crew/passengers/others), damage to property (ships/cargo/other), and/or pollution of the environment.

2.2 The reasons for shipping accidents

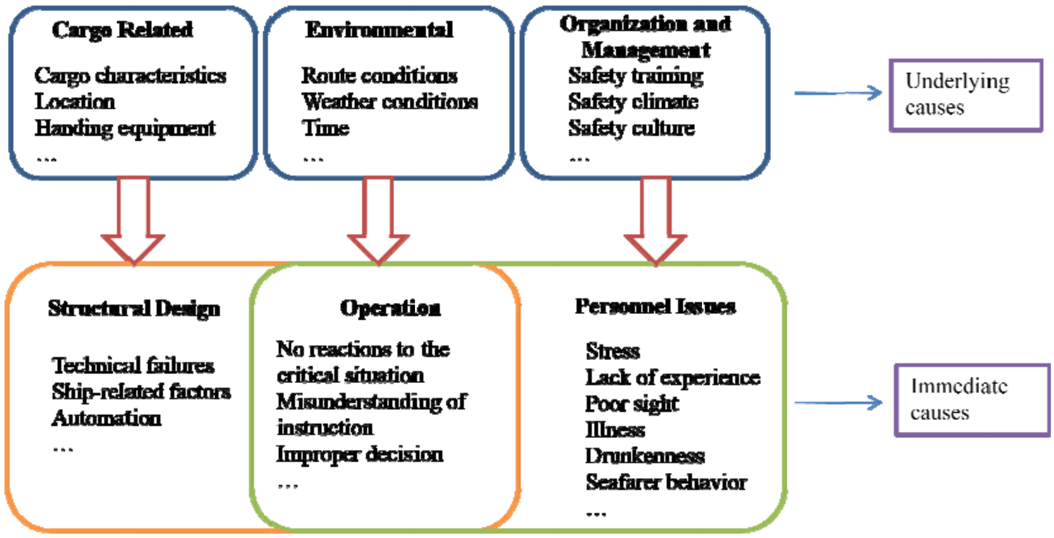
In addition to identifying the hazards related to an activity, the causes of such undesirable outcomes must be identified; the knowledge of such causes can then be used to prevent further shipping accidents from happening, thus assisting with risk control.

Identify risk causes are widely used in hazardous industries. An accident is the result of a complex interaction between design, operational and human performance (Mengolini and Debarberis, 2008). Therefore identify risk cause were consider aspects of the different layers that contribute to the safety of a hazardous industries.

A change in the “safety paradigm” has taken place in the last 30 years: Firstly the attention focus on the technical aspects shifted to human error and then to safety culture issues (Mengolini and Debarberis, 2008). Safety culture can provide indications of the safety awareness of one organization. However, identification of suitable indicators for safety culture is a difficult process (Marono, et al., 2006; Olive, et al., 2006; Vinnem, et al., 2006).

Similar, the reasons for shipping accidents are many and complex. In general, a casualty is the result of several causes—or, more correctly, an unwanted chain of events. In broad terms these are called immediate causes and underlying causes (Hetherington, et al., 2006). Structural design, personnel issues and their overlap, operational issues, belong to immediate causes. Cargo related issues, environmental issues and organization and management issues are underlying causes (Figure 2-1).

Figure 2-1: Causal factors associated with marine accidents



The Transportation Safety Board of Canada (1998) published a statistical analysis, and found that 74% of the accidents at sea can be attributed to human errors, 16% to technical failure, and 4% to environmental reasons.

Similar results are identified by the Maritime Safety Authority of New Zealand (1995-1996): 49% of shipping incidents have human factors cited as the cause, whilst 35% cite technical factors and 16% cite environmental factors.

2.2.1 Structural design

Researchers initially applied risk assessment to the improvement of a ship's structure through the process of design and shipbuilding. Two types of structural causes were studied (Akten, 2006). The first was technical failures, which are shortcomings within the ship itself, such as corrosion, engine failure or hull failure, arising from defective materials or construction.

Risk assessment was initially applied to the improvement of a ship's structure through the process of design and ship building. Stability theory and reliability theory have been developed and aimed at these kinds of problems.

Stability theory has been used to develop probabilistic resistance. Watertight compartment was one of the earliest examples in which probabilistic assessments of risk of failure were made. Water intake can only be controlled by subdividing the ships into watertight compartments, so that there are always enough intact ones to provide the necessary buoyancy. Wendel (1968) initially discussed this problem. Tagg (1982) investigated the probability of survival for different types of ships. Abicht (1989) extended the concept to assess the effect of subdivisions on the expected oil outflow from damaged tankers. A recent research direction concerns design configurations and the probability of oil outflow if collision or grounding occurs.

Reliability theory has been used to quantify the probability of structural failures and the contribution that different components make to such failures. Attempts to simplify design problems by the application of reliability based methods started in the 1970s (Mansour, 1972). For example, fatigue cracks may often threaten watertight integrity, and reliability approaches have been used to quantify the risk of crack growth and to plan maintenance. Soares (1998) reviewed these previous studies.

2.2.2 Human errors

Human causes are directly related to personnel and a crew's competence, these including a lack of adequate knowledge and experience, technical inability, a bad look-out, not paying proper attention to procedures and rules, carelessness in commanding a ship, fatigue and lack of alertness, being overworked, tiredness, having insufficient rest periods, and so on. Human errors were regarded as the heart of accident problem and the methods of control risk must be directed toward human failure (Heinrich, et al., 1980).

There are numerous citations indicating that 75-90% of accidents are rooted in human error (Talley et al., 2005; Rothblum, 2000; O'Neil, 2003; Esbensen, et al., 1985; Wagenaar and Groeneweg, 1987). The resolution of technical problems, such as by using enhanced navigational aids, has decreased the level of machine related errors, and this appears to have revealed the relative contribution of human errors in accident causation (Hetherington, et al., 2006).

The concerns about human errors have motivated the introduction of the International Safety Management (ISM) code. The ISM code is concerned with poor management standards and the contribution of human error and management shortcomings as a result of marine casualty investigations. When a common understanding is established as to the main causes of accidents, the clauses that form the ISM code can be linked to these causes as potential preventive measures, and it is planned that an expert panel shall make an estimation of the various preventive measures. So the scope of the ISM code is directly related to personnel and crew competence and to general operational aspects of shipping.

2.2.3 Operation

Operational issues are the overlap of structural design and human elements, which may include there being no reaction to a critical situation, a misunderstanding of instructions, or improper decisions.

The reasons for operational mistakes include inadequate communication, inadequate general technical knowledge and inadequate knowledge of a ship's own system (Rothblum, 2000).

As shown in Figure 2-3, 45% of accident reports determine the judgment (mistake) of ship masters and pilots as the predominant causes; in another 42% of cases, human errors refer to a lack of comprehension between the pilot and the master, inattention of the pilot and of the officer of the watch, or lack of communication among crew members (Trucco, et al. 2008).

Another operational mistake is inadequate general technical knowledge. Wagenaar and Groeneweg (1987) pointed out that this problem was responsible for 35% of casualties. Lack of knowledge of the proper use of technology was the main contributory factor in this category (Rothblum, 2000).

A frequent contributing factor to marine casualties is inadequate knowledge of own-ship operations and equipment. Several studies and casualty reports have warned of the difficulties encountered by crews and pilots who are constantly working on ships of different sizes, with different equipment, and carrying different cargoes. The lack of ship-specific knowledge was cited as a problem by 78% of the mariners surveyed (NRC, 1990).

2.2.4 Dangerous cargo

Dangerous cargoes such as oils and chemicals at sea have the potential for surrounding a vessel and catching fire. Romer et al. (1995a) found that accidents involving marine transport of dangerous goods have a larger proportion of accidents than other transport modes.

2.2.5 Natural conditions

Some maritime accidents occur due to unexpected and dangerous sea conditions, which can result in an inability to keep the ship under proper control (Toffoli et al., 2005).

Since ships spend long periods of time in transit from port to port, they are more exposed than other forms of transport to the effect of natural phenomena (Fukushima, 1976). Currents, tides and tidal streams, typhoons, stormy seas and so on, make for treacherous working conditions, and darkness, fog, heavy snow and rain reduce visibility for those people in control of a ship. Maritime accidents caused by abnormal weather conditions have resulted in many deaths and many persons have gone missing.

2.2.6 Route conditions

Narrow channels with abrupt and angular windings, as well as shoals and reefs, present navigational hazards (Fukushima, 1976). In these narrow areas, such as straits and channels, congestion may also become a cause of marine casualties.

Romer et al. (1995b), through a review of the frequency of collisions and groundings in the Great Belt, the Dover Strait, the Mexican Gulf, the US part of the Atlantic Ocean, Tokyo Bay, Porsgrunn harbour area and the Brevik/Stathelle place, found that the narrower the waters the higher the frequency is of groundings and collisions.

Quon and Bushell (1994) modeled the accident frequencies in Canadian waters, and confirmed that traffic density and the geographical environment are important factors in predicting the number of navigational accidents.

2.3 Risk management and decision-making

Since the 1990s, many maritime industrial sectors have been moving towards a risk-based 'goal setting' regime, where risk assessment researchers and safety engineers are motivated to develop and apply a variety of risk modeling and decision-making techniques (Wang, 2006). The tendency now is that risk assessment is not only used for verification purposes in design and operational processes, but also for making decisions right from the early stages (Wang and

Trbojevic, 2006).

More recently, several risk management and decision-making approaches were described for analyses of event probabilities and consequences.

2.3.1 HSE tolerability of Risk approach

The Health and Safety Executive (HSE), the UK offshore safety regulatory body, has presented a risk assessment method for decision making on safety issues. The HSE's approach is based on a tolerability of risk (TOR) framework (Figure 2-4), which has been adopted by most of the offshore operators (HSE, 2001).

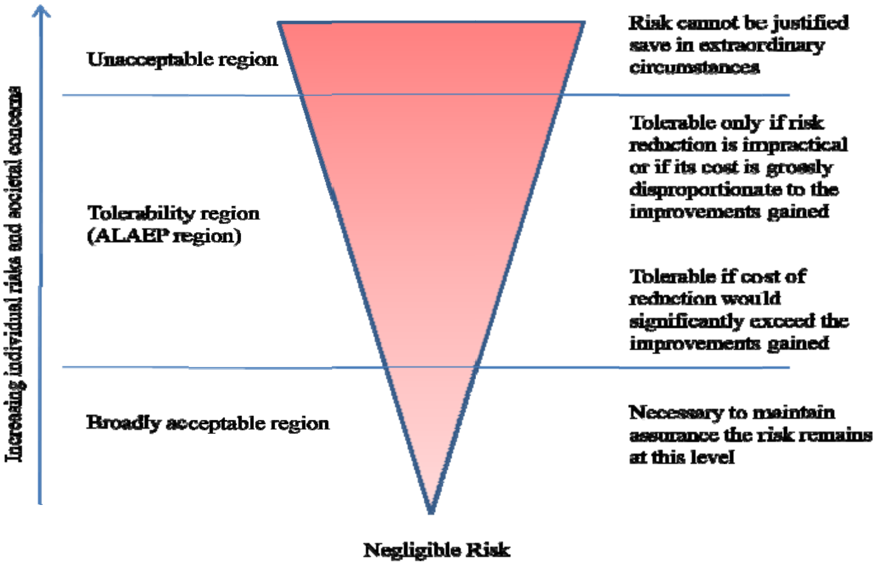
It divides risk into three regions:

Unacceptable: Risks regarded as unacceptable except in extraordinary circumstances, such as wartime, whatever their benefits. Activities causing this type of risk would be prohibited, or would have to have the risks reduced irrespective of the cost.

Tolerable: Risks that are tolerated in order to secure certain benefits. Risks are kept as low as reasonably practicable (ALARP) in this region, unless the cost is grossly disproportionate to the reduction in risk that they achieve.

Broadly acceptable: Most people regard these risks as insignificant and further action to reduce such risks is not normally required.

Figure 2-2: Tolerability of risk framework (HSE, 2001)

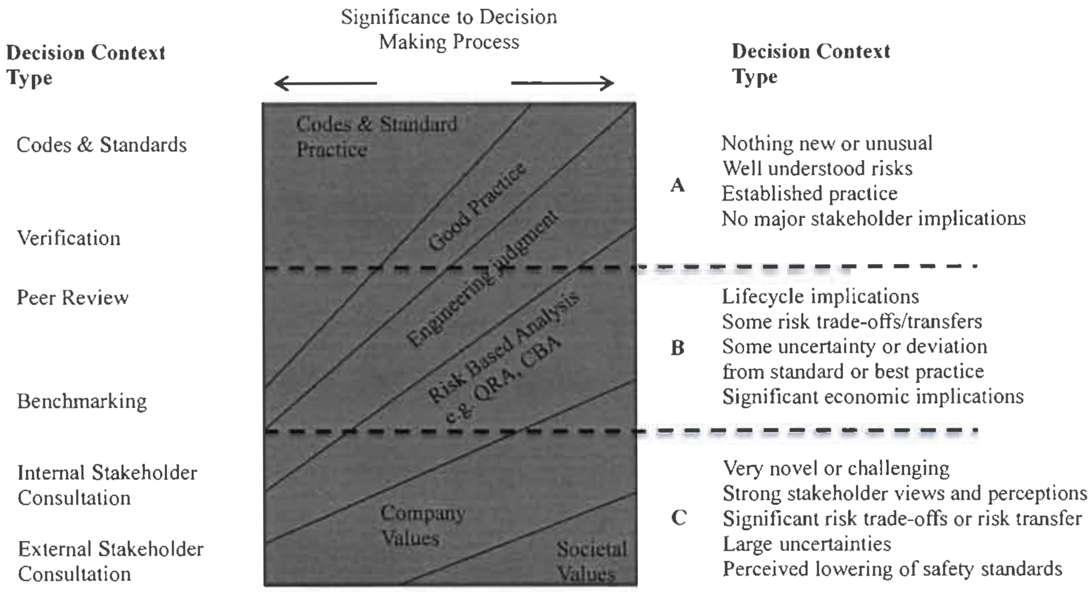


In order to apply it, the safety manager must first ensure that the risks are not unacceptable, and must then show that the risks are either ALARP or broadly acceptable.

2.3.2 UKOOA framework for risk related decision support

In 1996, the UK Offshore Operators Association (UKOOA) developed a framework to assist with risk related decision support (UKOOA, 1999). The aim was to help decision-makers choose an appropriate basis for their decisions.

Figure 2-3: The UKOOA framework (Wang, 2006)



The full spectrum that the framework takes for the decision bases ranges from those decisions dominated by purely engineering concerns to those where company and societal values are the most relevant factors (DNV, 2001).

The right hand edges of the framework (Figure 2-5) indicate the decision context, which can be used to help the user determine the context for a specific decision. Once this level has been identified, reading horizontally across the framework shows the suggested balance of decision bases to be taken into account in making the decision. The left hand side of the framework provides a means of calibrating or checking the decision basis (UKOOA, 1999).

It should be noted that the framework produced by the UKOOA is only applicable to risks falling within the ALARP region (Wang, 2006).

2.3.3 Formal Safety Assessment

In 1993, a standard analysis approach, the Formal Safety Assessment (FSA), a rule-making process for international shipping, was introduced to the IMO by the United Kingdom (MSC62/24/3, 1993) and was adopted by the IMO in 1995.

The FSA is defined as a structured and systematic methodology aimed at enhancing maritime safety, including the protection of life, health, the maritime environment and property, by using risk and cost-benefit assessments (MEPC 40/16/Cire. 335, 1997).

The main purpose of the FSA is to provide a more systematic and proactive basis for the IMO rule-making process (Kristiansen, 2005). The FSA comprises the following classic five steps within the IMO decision-making procedures (Wang, 2006):

Step 1: Identify and generate a selected list of hazards

Step 2: Risk assessment

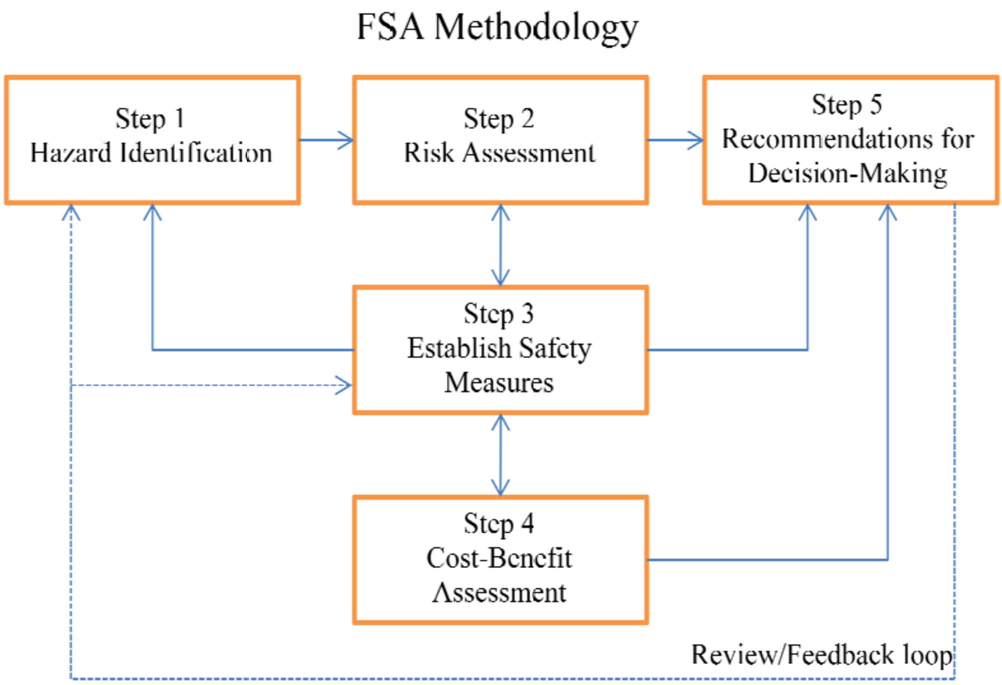
Step 3: Risk control options

Step 4: Cost-benefit assessment of each risk control option

Step 5: Make decisions and give recommendations for safety improvement

In reality, the interactions between the five steps of the FSA methodology are not so simple. The result and finding in each step are often used as feedback and input into several other steps (Kristiansen, 2005), these being described in Figure 2-6.

Figure 2-4: Flow chart showing the FSA approach



FSA is a new methodology in marine safety that involves using the techniques of risk and cost-benefit assessment to assist in the decision-making process (Wang, 2006). Within the IMO several FSA trial applications have been performed to provide support for the formulation of international regulations (DNV, 1997; IMO, 1997, 2000, 2002a, b).

As stated by Wang (2001), it is considered that “marine safety may be significantly improved by introducing a formal ‘goal-setting’ safety assessment approach, so that the challenge of new technologies and their application to ship design and operation may be dealt with properly". FSA involves a greater number of scientific aspects than previous methodologies. An ideal FSA has been characterized as having the following benefits (Wang, 2006):

- A consistent regulatory regime that addresses all aspects of safety in an integrated way;
- Cost-effectiveness, whereby safety investment is targeted to where it will achieve the greatest benefit;
- A pro-active approach, enabling hazards that have not yet given rise to accidents to be properly considered;
- Confidence that regulatory requirements are in proportion to the severity of the risks;
- A rational basis for addressing new risks posed by ever-changing marine technology.

However, such methods may be criticized in a number of ways: They oversimplify the systems studied; a number of failure combinations are overlooked due to the sheer magnitude of the problems; and operator omissions (such as forgetting or overlooking something) are not addressed in these models (Kristiansen, 2005).

The availability of suitable data necessary for each step of the FSA process is very important, and most of the time such data is not available. Lack of reliable safety data and lack of confidence in safety assessment have been two major problems in safety analyses (Wang, 2001). So expert judgment, physical models, simulations and analytical models may be used to achieve valuable results (Soares and Teixeira, 2001).

2.4 Overall risk level

As mentioned above, risk is defined as a measure of the probability of a hazard-related incident occurring, and the severity of harm or damage that could result (Manuele, 1997). So the Risk (R) can be expressed as a function of the severity of the possible consequences (S) and the probability of occurrence (P) for a particular hazard.

Li and Cullinane (2003) follow this concept and construct a maritime risk, as shown in the following formula:

$$R_i = S_i P_i$$

where R_i represents the risk associated with a particular hazard i, S_i represents the likely severity associated with succumbing to the hazard, and P_i is the probability of occurrence of such a maritime hazard at a given time period.

Secondly, based on the concept of particular risk, the concept of total risk picture for a given ship or fleet is quantified by the following relationship (Li and Cullinane, 2003):

$$R = \sum_{i=1}^{n} s_i p_i \,, i = 1, 2, \cdots n$$

where n represents the total number of hazards encountered or that are possible to be encountered.

Kristiansen (2005) developed a more complex framework to construct the total risk picture for a given activity or system. The framework breaks down the total risk picture into different phases of relevant risk scenarios.

$$R = \sum_{i} \sum_{j} s_{ij} p_{ij}$$

where i is the number of scenarios that may lead to a particular consequence*;* j is the number of phases within each accident type; s_{ij} is the consequence measure for the i type of shipping accidents at the j phase; and p_{ij} is the probability of the relevant consequences s_{ij} for the i type of accident at the j phase.

Using these equations, we can better understand risk. A high consequence (S) with a high probability (P) for a certain given hazard means that the risk is high. On the other hand, a low consequence (S) and a low probability (P) represent a low level of risk. So safety can be improved by reducing the risk, and risks can be reduced by reducing the severity of the consequences, reducing the probability of occurrence, or by a combination of the two (Kristiansen, 2005).

2.5 The probability P

In theory, total risk analysis of a vessel would entail the estimation of probability and consequence, which are extremely difficult to implement in practice. One main reason is that the calculation of the probabilities of shipping accidents is very difficult, since shipping accidents are typically very rare events (Gaarder, et al., 1997).

2.5.1 Statistical analysis

Traditionally, the most common way to estimate the probability of accidents has been to study accident frequency, this being regarded as the first type of study to address safety levels (Soares and Teixeira, 2001).

Studies based on shipping accident statistics provide an overall view of the levels of safety involved in the shipping activity through the frequency of casualties, which implies the hypothesis that risk levels existing in maritime transportation can be estimated through analysis of shipping accident statistics.

Statistical methods used in those researches mainly include: Mean, weighted mean and median.

2.5.1.1 Mean, weighted mean

Sample mean for N observations with value X_i is widely applied to compute the mean accident frequency rate. Or, if the variable is grouped observations, then the weighted mean may be more relevant.

Statistics about the frequency of accidents provide a primary view of safety performance, and numerous studies have contributed to this topic. Romer et al. (1995b) made a detailed review and comparison of this type research. Most of these studies have used accident frequency as a safety measure for examining the relationship between safety performance and one particular aspect, for instance, vessel age (Faragher et al., 1979; Cashman, 1977) or vessel flag (Li and Wonham, 1999; Pronce, 1990). Some are focused on a particular vessel type (Grabowski et al., 2007; Talley, 2001, 2002; Talley and Kite-Powell, 2006; Wang et al., 2005) or a particular business line (Mostafa, 2004). The results of previous studies provide useful insights into the influential characteristics of accident frequency.

2.5.1.2 Median

The median is the middle of a distribution—half the scores are above the median and half are below the median. The median is less sensitive to extreme scores than the mean, and this makes it a better measure than the mean if there are highly skewed distributions. Ponce (1990) found the median age for vessels totally lost is higher than the median age for the vessel population, which indicated that age statistically has an influence on vessel losses.

2.5.1.3 Probability distributions

There are two types of probability models that have been used: discrete and continuous distribution. Poisson distribution, one of the discrete distributions, is often used as a model for the number of events in a specific time period. In risk analysis, it does become widely applied.

Cariou et al. (2008) uses 4080 observations from the Swedish Maritime Administration (1996–2001) to investigate whether a ship that has undergone PSC inspection at a certain time exhibits a reduction in the total number of deficiencies detected during the next control. Poisson models were used in this research and they found that the age of the vessel, the ship type, and the flag of registry appear to be significant predictors.

Normal distribution is one of continuous distributions. The variable $X \sim N(\mu, \sigma^2)$ means X is normally distributed with mean μ and variance σ^2.

2.5.1.4 Time series statistics

Time series statistics of the number of vessel accidents present a useful measure of safety performance.

Li and Zheng (2008), through analyzing the total loss number and the total loss rate from 1973 to 2003, found that both of them have been steadily reduced, particularly since the introduction of the Port State Control program.

However, accident records alone cannot determine whether the accident rate has increased or decreased, as the number of accidents is also affected by the number of vessels and the number of trips per vessel.

The scarcity of accident statistics creates limitations. Firstly, statistics that describe the relationship between the characteristics and the accident does not describe the degree of influence of the frequency determining factors. Secondly, specific criteria, assumptions and factors examined are applied in most of the statistical analyses, and these may not be easily compared with other sources (Romer et al., 1995b). Thirdly, statistics describe only the past, and may not be useful in predicting the occurrence of a future accident, this being due to the fact that maritime accidents are typically very rare events (Chang and Yeh, 2004; Gaarder et al., 1997). Fourthly, just because no accidents have occurred in a specific highly sensitive area, it does not mean that the probability of an accident in that area is zero. An essential problem with accident statistics is the lack of standard procedures for storing accident information. For example, accidents are classified in alternative ways in different databases. In addition, it is impossible to estimate how, for instance, new safety measures would change the risk level based on the analysis of statistics.

2.5.2 Expert judgments

In practice, expert estimation is another common way in risk analyses having little or no relevant historical data.

As mentioned above, risk analysts have traditionally used historical data as the basis of information for frequency and probability assessments. A large number of databases need to be established for this purpose from different sources. However, an important factor is that a risk analysis typically deals with rare events, so relevant data will be scarce. Furthermore, the systems under study often represent new concepts and arrangements where little or no experience exists, so the use of expert judgments is obligatory (Apeland and Aven, 2002).

Based on the experts' training and experience, expert judgments can provide useful information for forecasting, making decisions and assessing risks. Expert judgments can be used in most steps involved in risk assessments: Hazard identification (Hu et al., 2007), risk estimation (Jones et al, 2009; Wang, 2001; Wang, 2006), risk evaluation and analysis of options (Pedersen 1995).

The expert judgment is typically appropriate when (Daneshkhah, 2004):

- Data is sparse or difficult to obtain. Sometimes information is not available from historical records, prediction methods or literature.
- Data is too costly to obtain.
- Data is open to different interpretations, and the results are uncertain (unstable). Models to analyze risks are not available.
- There is a need to perform an initial screening of problems.

However, there are some typical problems associated with using subjective probability, provided by expert, as a measure of uncertainty in risk analysis.

Firstly, experts often fail to consider all possibilities with respect to human errors affecting technological systems (Slovic et al, 1979).

Secondly, overconfidence in current scientific knowledge is common (Slovic et al., 1979). Over and under confidence are typical characteristics of an expert's confidence in his/her own judgments (Skjong and Wentworth, 2001).

Thirdly, experts are easily affected by operational experience (Skjong and Wentworth, 2001). Experiencing an accident, or a near-miss accident, makes a person biased with respect to that risk. Such an experience will cause the person to overestimate the risk.

In addition, experts' judgments are superficial and imprecise because of heuristics and biases (Kahneman, 1982). Those biases may be interpreted as mechanisms that create inconsistency between the expert's knowledge and his/her assessment of uncertainty, or a disparity between the perceived uncertainty and the probability figure (Apeland and Aven, 2002).

Skjong and Wentworth (2001) reported that experts are subject to similar biases as lay people. Even though they may not be influenced in the same manner or to the same extent, expert judgments should be utilized with great caution.

Nevertheless, as noted by Anderson et al (1999), expert judgment must be used with care. Kahneman et al. (1982) discuss the numerous biases and heuristics that are introduced when humans process information and attempt to provide judgments.

2.5.3 Logistic regression

Logistic regression (sometimes called a logistic model or logit model) is used for prediction of the probability of occurrence of an event by fitting data to a logit function logistic curve.

2.5.3.1 Development of Logistic regression

The logistic model was initially introduced by Berkson (1944), who derived the logit model used in bioassay studies. The goal of logistic regression is to identify the best fitting model that describes the relationship between a binary dependent variable and a set of independent or explanatory variables (Washington et al., 2003).

Logistic regression can be used to determine the effect size of the independent variables on the dependent; to rank the relative importance of independents; to assess interaction effects; and to understand the impact of covariate control variables. The impact of predictor variables is usually explained in terms of odds ratios. Barnard (1949) developed the term Log-odds in the context of Berkson's logit model. Given that p is the probability of success, the odds of success is defined as $p/(1-p)$. The log-odds is $\ln\left(\frac{p}{1-p}\right)$, which plays an essential role in logistic modeling. The log-odds is the linear predictor $x\beta$ of the binary logistic model.

2.5.3.2 Advantages

The logistic regression model is most often a superior approach which developing models of event outcome or qualitative choice, for a number of reasons.

Firstly, it is more robust to violations of assumptions of multivariate normality and equal variance-covariance matrices across groups (Dawes et al, 1997). So the logistic regression approach does better when there is evidence of substantial departures from multivariate normality, as is the case where there are some dichotomous or zero/one variables, or where distributions are highly skewed or heavy-tailed (Green et al, 1998). Secondly, the logistic regression equation ensures the predicted values of the dependent variable to lie in the interval between zero and one (Karp, 1998). Thirdly, the odds ratio, a simple transformation of the logistic regression model's parameters, leads to an easily interpretable and explainable quantity (Karp, 1998). Finally, a logistic regression model can generate estimates parameter be applied to create a probability of event outcome for each "member" of the population.

2.5.3.3 Disadvantages

Fensterstock (2005) identifies some disadvantages of logistic regression. Firstly,In many cases preparation of the variables takes a long time. Secondly, with many variables the analyst must perform a pre-selection of the more important ones, based upon separate analyses. Finally, some of the resulting models are difficult to implement.

2.5.3.4 The application of Logistic regression

Logistic regression has proven to be a powerful modeling tool for prediction of the probability of occurrence of an accident, by fitting data to a logit function logistic curve. In recent years logistic regression has been suggested as an appropriate analytical technique to use for the multivariate modeling of categorical dependent variables.

The logistic regression model has been used in many disciplines, including maritime studies. It has been used extensively in epidemiological research (Levy and Stolte, 2000; Ottenbacher et al., 2004), in social sciences research (Candido et al., 2009; Saijo et al., 2008; and Garcia-Ramirez et al., 2005). It has also become an important tool in commercial applications. The two most commonly studied topics were consumer behavior and international marketing (Akinci et al., 2007).

There are some researchers in the maritime domain that have used the logistic regression model. Bergantino and Marlow (1998) used a logistic regression model to analyze the decision-making process of shipowners when adopting flags of registration. This paper provided indications of the likelihood of a particular vessel being flagged out under different circumstances, and further considered how changes in these circumstances might affect the probability of the event occurring.

Jin et al. (2002, 2005) developed a fishing vessel accident probability model for fishing areas off the northeastern United States using logistic regression and their database. Knapp and Franses (2007) used binary logistic regression to measure the effect of inspection on the probability of casualty.

2.6 Consequences

Any one failure might lead to different consequences with different degrees of seriousness, including: Accident, incident, operating disturbance and non-conformance (Kristiansen, 2005).

An accident is defined as an undesirable event that results in damage to humans, assets and/or the environment. An incident is defined as an undesired event that is detected, brought under control or neutralized before it results in accidental outcomes. An operating disturbance is defined as a situation where the operating criteria for a system or component are violated. A non-conformance is defined as a situation in which the operation is outside certain criteria that have been determined as acceptable (Kristiansen, 2005).

In this study, the term shipping accidents refers to the first category of shipping accidents, i.e. accident. Incidents, operating disturbances and non-conformances are not included. That is because this kind of information cannot be obtained from public resources, even though such information on incidents, operating disturbances and nonconformance is useful for maritime safety management.

2.6.1 The harm of the hazard

In the context of safety, an undesirable outcome could include injury to personnel, damage to property, and/or pollution of the environment.

The capsizing of the 'Herald of Free Enterprise' resulted in at least 150 passengers and 38 crew members losing their lives. The RO–RO passenger ferry 'Estonia', carrying 989 people, sank in the northern Baltic Sea, and only 137 passengers survived. The Scandinavian Star disaster in 1990 resulted in the loss of 158 lives. Those accidents highlighted the role of human error in marine casualties and, as a result, the new Standards for Training, Certificates and Watch-keeping for seafarers were subsequently introduced.

In recent times there has been an increasing focus on the environmental aspects of maritime activities. Ships are polluting both the marine environment and the atmosphere. The main problem has been the spilling of oil related to cargo operations and tank cleaning. The Exxon Valdes accident in 1989 seriously damaged the environment by the large scale oil spill, and this disaster cost Exxon $2.2 billion in clean up costs alone.

2.6.2 Consequence estimation

The consequences, the various consequences types and the severity classification, are very important when qualifying the safety (or the risk). There are a number of factors that affect the extent of damage, including the structural characteristics and mass of the vessels involved their speed and relative course, and the location of any damage (Kristiansen, 2005).

Environmental damage is more difficult to assess. The number of endangered species and the area of contaminated soil, or even the length of polluted shoreline, can be used when assessing the environmental damage.

Money is in many cases a well-known measure and the total amount of costs involved are often used when capital or property losses due to accidents are assessed.

2.7 Risk Analysis techniques

When both the frequency and the consequence of each hazard have been estimated, they are combined to form measures of overall risk. There is a wide range of different risk analysis models, but a universally applicable, uniform theory is still lacking (Harms-Ringdahl, 1993). Several models have been developed to serve the different purposes in the different frameworks (Manuele, 1997). The deficiencies of each model should always be considered.

2.7.1 Fault tree analysis

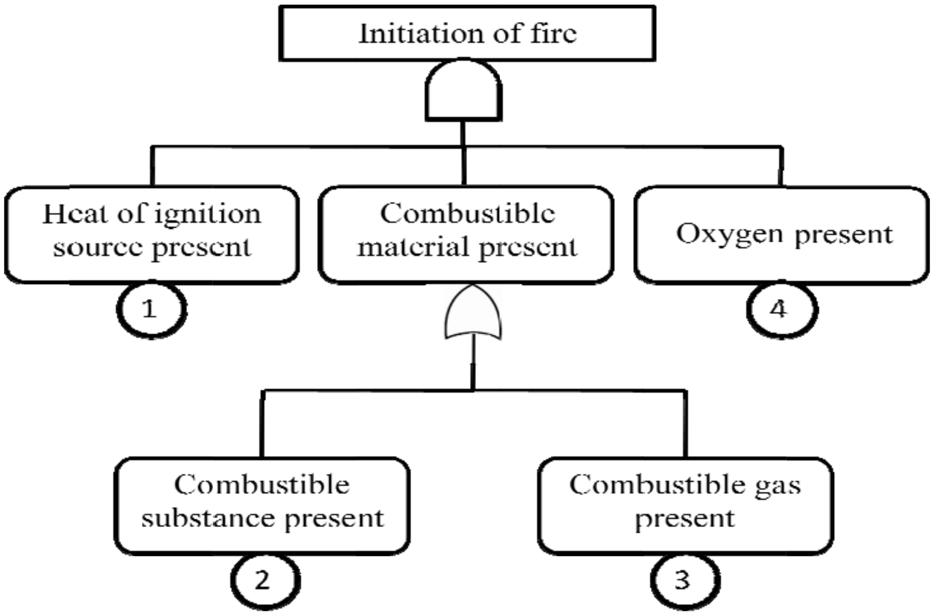
The fault tree model is one of the most frequently used techniques in risk analyses, and started to be developed in 1962 by H. S. Watson. The fault tree is a visualization of the relationship between the causes of an accident by use of a logical diagram (Figure 2-7).

Descriptions of the method are presented, for example, in Vesely et al.

(1981) and Kumamoto & Henley (1996). The fault tree model can often be utilized even for a quantitative risk analysis of the accident probability, a complicated technical system if the probabilities of the “failure events” are known.

Binary operation modes are assumed in this method, which means that an event either occurs or it does not. So, based on the use of AND and OR gates (Vesely et al., 1981), this method is well known and widely applied.

Figure 2-5: A fault tree diagram



It has been claimed that the more unusual accidents cannot be captured by a fault tree, because there are usually too many conjunctive conditions (Reason et al., 2006). Also, the method assumes binary operational modes, so degraded operations or events cannot analyze in fault trees (Kristiansen, 2005).

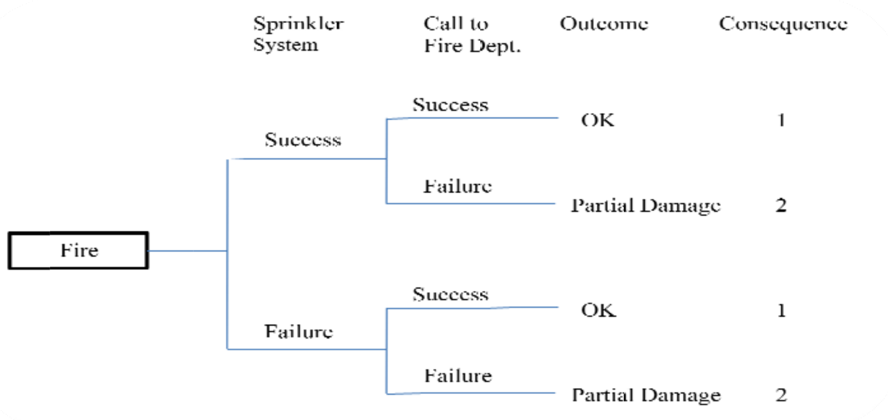
It has also been criticized for being difficult to use (Harms-Ringdahl, 1993). It may not be a suitable model for the analysis of man-machine interaction, or for the analysis of an organization (Harms-Ringdahl, 1993).

2.7.2 Event tree analysis (ETA)

The event tree is an inductive method, and can be described as being the opposite of a fault tree. An ETA splits up a given initiating event forwardly and then describes all the possible consequences of this, taking into account whether installed safety barriers are functioning or not, as well as additional events and factors (Figure 2-8).

The ETA can be used to identify all potential accident scenarios and sequences in a complex system. Design and procedural weaknesses can be identified, and probabilities of the various outcomes from an accidental event can be determined.

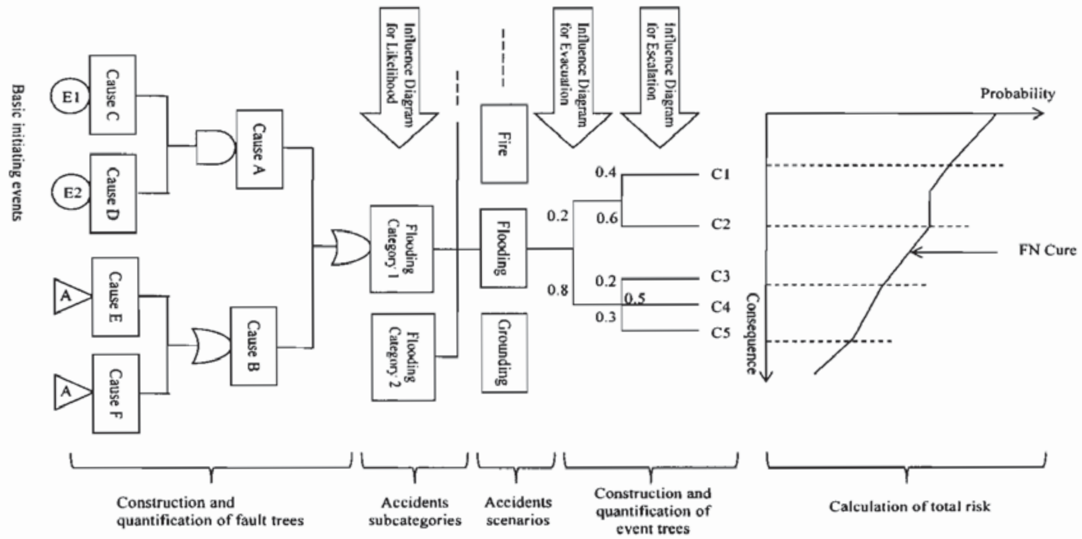
Figure 2-6: An event tree diagram



2.7.3 Cause/Consequence model

A fault tree and event tree can often be used together (Figure 2-9). The fault tree is used to quantify the probability of occurrence for a certain accident, while the event tree is used to quantify the frequency of different consequences given a certain accident outcome.

Figure 2-7: An integrated risk assessment diagram



This kind of model can be developed either as a qualitative model or as a quantitative model. The latter option is possible if the fault trees and event trees can be equipped with quantitative data related to the risk contributors (Kristiansen, 2005).

The potential consequences should reflect the injuries to people, as well as damage to both the environment and physical assets.

Extensive knowledge of the system and situation under consideration is needed in order to create reasonable and valid event and fault trees. The risk is calculated by combining the probabilities of occurrence with the severity of the consequences. If this is done for all possible outcomes of an accident scenario, the total risk picture is established.

So then, the risk contribution tree may be used for focusing the risk control options on areas where their impact is greatest, and do it in a cost-effective way. The possibilities for improving the outcome decrease the probability and/or the consequences, depending on the stakeholder. A crew member, the ship designer, the owner of the ship and the administrator do not have similar alternatives available for risk reduction. However, by the use of proper risk models it becomes easier to select the best alternative(s) in each case.

2.7.4 Bayesian Network (BN)

The Bayesian Network (BN) is a method that has been developed to improve the understanding of the effects of different causes on the risk (Netjasov and Janic, 2008).

2.7.4.1 Definition of BN

The BN is based on the probability theory and use of Bayes's rule/theorem (Bayes, 1763) as its rule of inference. This subjective probability theory is only part of the Bayesian inference mechanism. Together with the applicable results of such probability concepts as the product and sum rules, the concept of conditional independence (Pearl, 1988), dependency separated or d-separated (Pearl, 1988), the techniques of marginalization (Vellido & Lisboa, 2001), and the pattern of inference (Wellman and Henrion, 1994; Lauritzen and Spiegelhalter, 1988; Pearl, 1988), it provides the basic tool for both Bayesian belief updating and for treating probability as logic.

2.7.4.2 Application of BN

Due to the development of propagation algorithms (Lauritzen & Spiegelhalter, 1988; Pearl, 1988; Russell and Norvig, 2003), followed by the availability of easy-to-use commercial software and a growing number of creative applications (Jensen, 1990; Marsh, 1999), BN has caught the sudden interest of researchers in various research fields since the early 1990s.

BNs have been applied in several areas, such as medicine, ecology, environmental impact assessment (Marcot et al., 2001; Matias et al., 2007), business risk and product life-cycle analysis (Zhu and Deshmukh, 2003) and, more recently, to handling data obtained as a result of prospecting for minerals and rocks (Rivas et al., 2007).

BNs have been applied in many areas, including risk assessment of building structures under fire (Gulvanessian and Holicky, 2001), manufacturing industries (Jones et al., 2009), workplace accidents (Martin et al., 2009) and business risks (Zhu and Deshmukh, 2003). Hayes (1998) applied BN successfully to ecological risk assessment. Kang and Golay (1999) applied BN successfully to fault diagnosis in complex nuclear power systems.

Applications using Bayesian Networks as a modeling tool in maritime applications have recently been widely demonstrated. Eleye-Datubo et al. (2006) used BN to examine a typical ship evacuation in an accidental risk scenario. Trucco et al. (2008) developed a Bayesian Belief Network to model the maritime transport system by integrating human and organizational factors into risk analysis. The conditional probabilities for the BN have been estimated by means of expert judgment. Ren et al. (2008) assessed offshore safety by combining Reason's "Swiss Cheese" model and BN. The prior probabilities were obtained by domain experts' judgments, but it has been found that BN modeling relying heavily on an expert's personal experiences may be error prone. Eleye-Datubo et al. (2008) examined the transfer of oil to an oil tanker. A BN model was created to examine system safety. In the research, given a certain event happening, it was possible to investigate other factors either influencing or being influenced by the event in the overall risk analysis. Friis-Hansen (2000) applied BN to maritime decision support, mainly regarding maintenance planning and risk-related issues.

2.7.4.3 Advantages

BN has several features:

- It has the ability to incorporate new observations in the network and to predict the influence of possible future observations onto the results obtained (Heckerman and Breese, 1996).
- It can not only let users easily observe the relationships among variables, but also give an understandable semantic interpretation to all

the parameters in a Bayesian Network (Myllymaki, 2005).

- It can handle missing and/or incomplete data. This is because the model has the ability to learn the relationships among its nodes, and encodes dependencies among all variables (Heckerman, 1997).

- It can conduct inference inversely (Ren et al., 2009).

- It adds consistency and transparency to risk models (Friis-Hansen, 2000).

- It enables different circumstances to be simulated and their effects on each of the variables, including the discrete qualitative variables, in play to be probabilistically analyzed (Matias et al., 2008).

2.7.4.4 Disadvantages

In spite of BN's remarkable power and advantages, there are some inherent limitations. A common criticism of the Bayesian approach is that it requires too much information in the form of prior probabilities, and that this information is often difficult, if not impossible, to obtain in risk assessment (Yang et al., 2008). The size of the internal conditional probability table (CPT) quickly becomes quite large when a child node is added, this being exponential to the number of nodes. The computations become complex and difficult (Eleye-Datubo et al., 2006).

2.8 Foundation of Port State Control (PSC) programs

Although the PSC is a fresh concept, there is currently a flourishing development of PSC programs. But most of them are about why PSC inspections should be implemented (Clarke, 1994) and how they should be implemented (Li, 1999; Florens and Foucher, 1999). Hare (1997) discussed how the proliferation of regional MoUs has significantly diminished the potentials for substandard ships to participate in international commerce. Cariou et al. (2008) applied a dynamic approach to test the effectiveness of PSC. They found that following a PSC inspection, the reported deficiencies during next inspection is reduced.

Few studies have investigated the inspection rate and the penalties.

In practice, existing tools assisting port inspection policies are varied, including essentially three "models". These include the target matrix method (practiced by the US Coast Guard), the shipping targeting system (Tokyo MOU Secretariat, 2004) and the inspection regime (Paris MOU).

Attempts to improve these "models" were conducted by Li (1999) and Xu et al. (2007). These "models" are "risk models" that seek to provide port state authorities with the means to identify ships that may have a propensity to deviate and thereby be preventively inspected. Other attempts have focused on the use of technological and management measures, or both. For example, an optimal monitoring technique combining satellite information was investigated by Florens and Foucher (1999). Gawande and Bohara (2005) analyzed an optimal contract which mixes penalties based on the amount of pollution ex post, with penalties based on the extent of noncompliance ex ante. Li and Cullinane (2003) pointed out the behavioral effects of shipowners and Port State authorities in such cases. An integrated inspection support system was investigated by Hamada et al. (2002).

These models were used to decide which ship should be inspected. How many of those ships should be inspected? Viladrich-Grau (2003) gave three reasons why an inspection policy in which the probability of being monitored is equal to one might not be optimal. Firstly, if vessels were to comply even when their probability of being monitored was strictly less than one, then one would not be the optimal monitoring frequency. In such a case, it would be possible to attain the same level of compliance with lower enforcement costs. Secondly, inspecting Priority III vessels with a probability of one would induce more Priority IV vessels to comply than that Priority I and II vessels would neglect maintenance. Finally, he thought that if the examination were to take place on a strictly deterministic basis, then a shipowner could be "cleaning up his act" only prior to a scheduled inspection. So he thought randomized inspections seemed more advisable.

What the optimal inspection level is, Viladrich-Grau (2003) did not mention. Judging from the literature, however, few attempts have been conducted to determine port inspection levels.

2.9 Game theory in environmental control

The theory of inspection game and their applications include for example, Avenhaus et al. (1994, 1995, 1996, and 2004), Baston and Bostock (1991), Canty et al. (2001), Maschler (1966), Von Stengel (1991) as well as Rothenstein and Zamir (2002).

Environmental control problems provide a field in which to apply game theory. One player is a monitoring agent whose responsibility is to detect or better prevent illegal pollution. The other player is a firm that produces a certain pollution (air or water), and which can save costs by illegal emissions. Both agents are assumed to act strategically. Various scenarios of this kind of problem have been analyzed. However, these papers do not yet address specific practical cases.

Bird and Kortanek (1974) explored various cooperative n-person game theory concepts in order to aid the formulation of regulations of sources of pollutants in the atmosphere related to given least-cost solutions.

Russell (1990) introduced a specific type of stochastic model by allowing for errors of inference on the part of the agency due to imperfect monitoring instruments. An one-stage game between a polluter and an environmental protection agency is used as a benchmark for discussing a multiple-stage game in which the source's past record of discovered violations determines its future probabilities of being monitored.

Gueth and Pethig (1990) analyzed a signaling game between a polluting firm that can save costs by illegal waste emission and a monitoring agent whose job it is to prevent such pollution.

A common assumption of former researches is that the game is zero-sum. Zero-sum describes a situation in which a participant's gain or loss is exactly balanced by the losses or gains of the other participant(s). This assumption is not reasonable in practice.

2.10 Limitations of maritime risk analysis

Risk analysis (and assessment) is a powerful tool used for obtaining information and increased understanding of a system, its hazards, and the accident mechanisms. This information and understanding enables us to implement risk control options and thus improve the system's safety.

However, the lack of good statistical data due to limited experience is probably the most significant and common limitation in quantitative analysis (Kristiansen, 2005). This is particularly clear in a maritime context, where the number of large scale accidents is quite low. Lack of statistical data results in huge uncertainties in the outcomes of the analyses, and one should therefore always evaluate these uncertainties and include this evaluation in the decision and recommendation process.

Secondly, most safety systems are extremely complex, which necessitates making several simplifying assumptions in order to be capable of performing the analysis. These simplifications also create uncertainties (Kristiansen, 2005).

This chapter revealed that shipping has always been a risk industry. To prevent unwanted events, such as occupational accidents, major accidents and disasters, risk and safety analysis or assessments are needed. In the theory, total risk analysis of a vessel would entail the estimation of probability and consequence. So safety can be improved by reducing the risk, and risks can be reduced by reducing the severity of the consequences, reducing the probability of occurrence, or a combination of the two.

However, the calculation of the probabilities of shipping accidents is very difficult. Traditional and the most common way to estimate the probability of accidents is to contemplate accident frequency, which be regarded has limitations. Expert estimation is another common way in risk analyses with little or no relevant historical data, but should be utilized with great caution (Skjong and Wentworth, 2001). Logistic regression has been proven to be a powerful modeling tool for prediction of the probability of occurrence of an accident.

The consequences, the various types of consequences and the various classes of their severity, are very important when safety (or the risk) is considered, which is difficult to assess. Money is in many cases a good measure.

When both the frequency and the consequence of each hazard have been estimated, they are combined to form measures of overall risk. Due to the fact that fault trees cannot directly accommodate dependent basic events they are not appropriate for the assessment of probabilities of scenarios involving so-called common cause failures. This limitation is, however, not present for Bayesian Network, which seem to be a very promising tool for risk analyses in general.

Chapter 3：Research Methodology

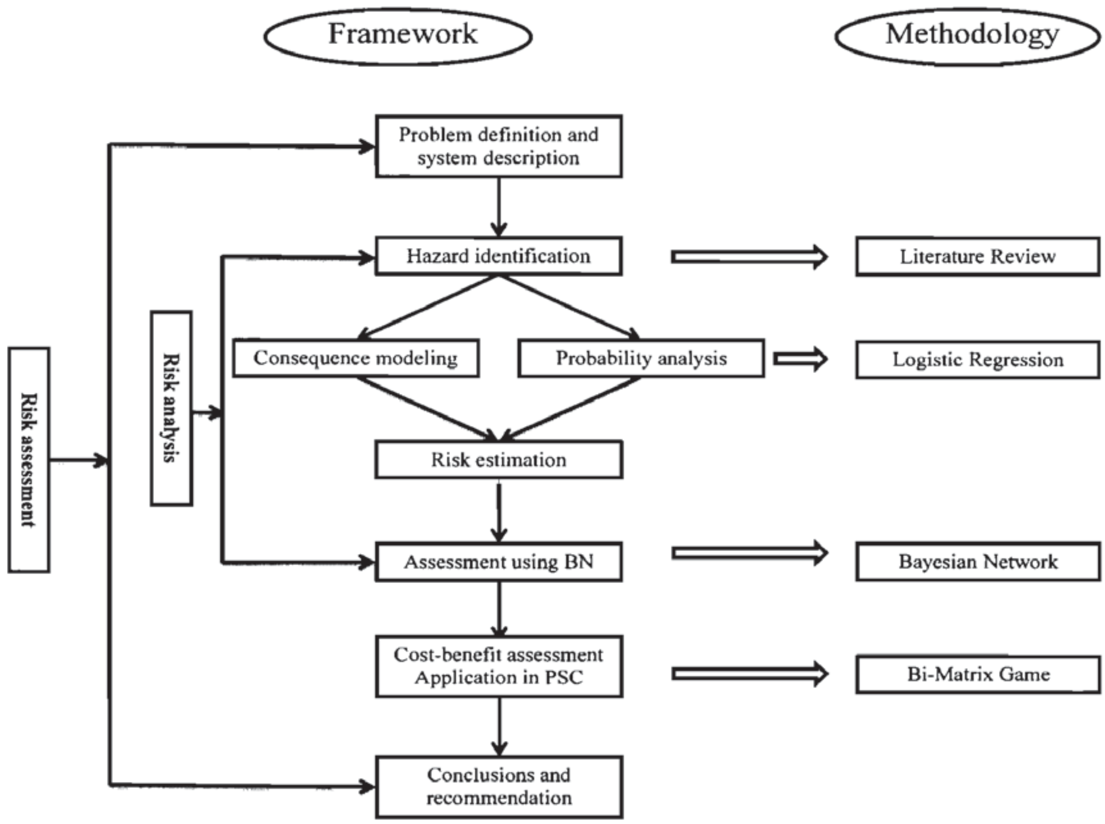
The literature review reveals that total risk analysis of a vessel entails the estimation of probability and consequence. Furthermore, the traditional and most common ways, based on frequency statistics and expert estimation, are regarded as having limitations. In this chapter, a methodology known as multivariate logistic regression is introduced to estimate the probability of a vessel having an accident. A Bayesian Network (BN) approach has been developed to model the effect of shipowners' efforts by taking into account different influencing factors and their mutual influences.

3.1 Research framework

The research problem defined in this study is investigated through the following research process shown in Figure 3-1. The left part of the Figure is the research process, and the right part is the corresponding research methodology.

Quantitative analysis and qualitative analysis are combined in this study. A literature review was performed primarily on relevant topics in maritime safety and casualty analysis, and which provides the basic indicators that would have an effect on the probability of accident. This thesis does not look into the root causes of accidents, due to the inadequate quality of accident data. This study focuses on the probability of accidents as a measure of safety performance. The quantitative parts of the thesis consist of logistic regression and a Bayesian Network, and a combination of the two. In the next part they are introduced separately.

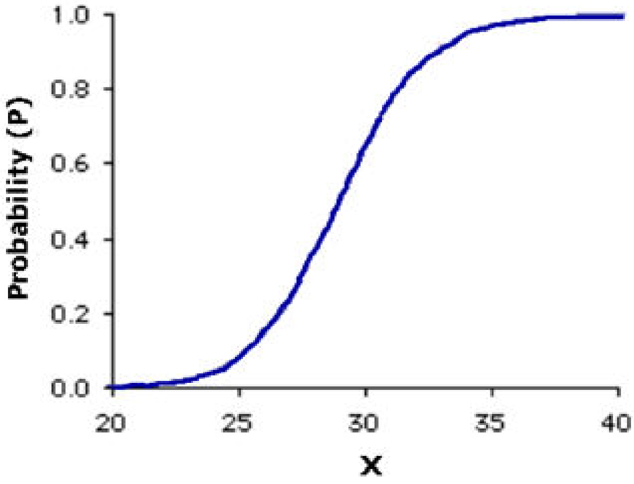
Figure 3-1: Research flow and research methodology



3.2 Logistic regression

In statistics, logistic regression (or logit regression) is used for prediction of the probability of occurrence of an event by fitting data to a logit function logistic curve (Figure 3-2).

Figure 3-2: Logistic curve



3.2.1 Odds and Log-odds

To appreciate the logistic model, it's helpful to have an understanding of odds and odds ratios. Most people regard probability as the "natural" way to quantify the chance that an accident will occur. The probability equal to 0 meaning that the accident will certainly not occur, and equal to 1 meaning that the accident certainly will occur. Odds is another ways of representing the chance of accident.

Odds is defined as the relationship of p the probability of accident ($y_i = 1$) to $1 - p_i$ non-accident ($y_i = 0$). The relationship is shown is symbolize as:

$$odds = \frac{p_i}{1-p_i} \qquad (3\text{-}1)$$

Suppose a probability value equal to 0.5. The odds, given the above formula, is 1. Unlike the probabilities, there is no upper bound on the odds.

The log-odds, or logit, is simply the natural log of the odds.

$$Logodds = logit = \ln\left(p_i/(1-p_i)\right) \tag{3-2}$$

As discussed earlier, a major problem with the linear probability model is that the probabilities are bounded by 0 and 1, but linear functions are inherently unbounded. Transforming the probability to log-odds removes the bound.

3.2.2 The logit model

The estimated probability (p_i) of a ship having an accident parameterize as an exponential function of shipping's operating characteristics. Suppose that for each vessel i traveling in a specific area, there is an observation y_i that takes two possible forms, accident ($y_i = 1$) or no accident ($y_i = 0$). The result is a binomial model since the y_i is one of two alternatives, therefore Logistic regression model was seclected, which is the foremost method used to model binary responses.

In a binary regression, a latent variable y_i^* is mapped onto a binominal variable y_i, where $y_i^* \in (-\infty, +\infty)$. While y_i^* is unobservable, y_i is observable:

$$y_i = 1 \ accident, if \ y_i^* > 0$$

$$y_i = 0 \ non-accident, if \ y_i^* \leq 0$$

Consider a random m-dimensional vector $X = (x_1, \cdots x_m)$. Each variable may be discrete having a finite or countable number of states, or continuous.

Defining the latent variable as a function of X

$$y_i^* = \sum \beta_i X + \varepsilon_i \qquad (3\text{-}3)$$

where β_i represent a column vector ofthe coefficients, describing the magnitude of the contribution of each risk factor.

This now gives:

$$E(y_i|X) = P(y_i = 1|X) = P(y_i^* > 0|X) = P(\varepsilon_i > -\beta_i X) = 1 - F(-\beta_i X)$$
(3-4)

In principle, any proper, continuous probability distribution of F defined over the real line (Figure 3-2) will suffice. The normal distribution (Probit model) and logistic distribution (Logit model) have been used in many analyses. Greene (2003) concludes that in most applications these two models seem not to make much difference, particularly if the sample contains very few responses (Ys equal to 1). For this study the logistic cumulative distribution function for F is chosen. The general model can therefore be written in the form

$$p_i = \frac{e^{\sum \beta_i X}}{1+e^{\sum \beta_i X}} \qquad (3\text{-}5)$$

Given the variables x_i, if one can observe the state of every variable in$X$, the conditional probability can be calculated using Equation 3-5.

From the above equations, it can be seen how logistic regression modeling is able to use a series of transformations to the dependent variable in order to allow it become continuous value with unbounded, but yet still be able to estimate a predicted probability that only falls between 0 and 1.

3.2.3 Estimation methods

Maximum likelihood estimation (MLE, or ML), is a very general approach for estimating the logit model for grouped data. ML estimators are consistent, asymptotically efficient and asymptotically normal in large samples (Allison, 1999). Consistency means that the probability that the estimate is within some small distance of the true value gets larger, as the sample size gets larger. Asymptotic efficiency means that, in large samples, the estimates will have standard errors that are, approximately, at least as small as those for any other estimation method. And finally, the sampling distribution of the estimates will be approximately normal in large samples, which means that you can use the normal and chi-square distributions to compute confidence interval and p values.

The basic principle of MLE is to choose as estimates those parameter values which would maximize the probability of observing current values of observations.

Firstly, the likelihood function need construct, which expresses the probability of observing the data in hand as a function of the unknown parameters. The likelihood of observing the values of y for all the observations can be written as

$$L = \mathrm{P}(y_1, y_2, \cdots y_n) \qquad (3\text{-}6)$$

Since individual observations are independent then equation can rewrite

$$L = \mathrm{P}(y_1)\mathrm{P}(y_2) \cdots \mathrm{P}(y_n) = \prod_{i=1}^{n} \mathrm{P}(y_i) \qquad (3\text{-}7)$$

By definition, $\mathrm{P}(y_i = 1) = p_i$ and $\mathrm{P}(y_i = 0) = 1 - p_i$ then

$$\mathrm{P}(y_i) = p_i^{y_i}(1 - p_i)^{1-y_i} \tag{3-8}$$

$$L = \prod_{i=1}^{n} p_i^{y_i}(1 - p_i)^{1-y_i} = \prod_{i=1}^{n} \left(\frac{p_i}{1-p_i}\right)^{y_i} (1 - \mathrm{p}_i) \tag{3-9}$$

For log of this function:

$$lnL = \sum_i y_i ln\left(\frac{\mathrm{p}_i}{1-p_i}\right) + \sum_i \ln(1 - p_i) \tag{3-10}$$

Substituting equations (3-5) into equation (3-10)

$$lnL = \sum_i \beta_i \mathrm{X} y_i - \sum_i \ln(1 + e^{\beta_i \mathrm{X}}) \tag{3-11}$$

Secondly, choose the value of β_i that make equation (3-11) as large as possible. Taking the derivative of equation and setting it equal to 0 gives us:

$$\frac{\partial lnL}{\partial \beta_i} = \sum_i \mathrm{X} y_i - \sum_i \mathrm{X}(1 + e^{-\beta_i \mathrm{X}})^{-1} = \sum_i \mathrm{X} y_i - \sum_i \mathrm{X} \hat{y}_i = 0 \tag{3-12}$$

Where $\hat{y_i} = \frac{1}{1+e^{-\beta_i \mathrm{X}}}$

Then iterative methods must used which amount to successive approximations to the solution until the approximations “converge” to the correct value. One of the most widely used iterative methods is the Newton-Raphson algorithm, which can be described as follows: let $U(\beta_i)$ be the vector of first derivatives of lnL with respect to β_i and let $I(\beta_i)$ be the matrix of second derivatives of lnL with respect toβ_i. That is,

$$U(\beta_i) = \frac{\partial lnL}{\partial \beta_i} = \sum_i \mathrm{X} y_i - \sum_i \mathrm{X} \hat{y}_i \tag{3-13}$$

$$I(\beta_i) = \frac{\partial^2 lnL}{\partial \beta_i \partial \beta_i{}'} = -\sum_i \mathrm{XX}' \, \hat{y}_i (1 - \hat{y}_i) \tag{3-14}$$

The Newton-Raphson algorithm is then

$$\beta_{i,j+1} = \beta_{i,j} - I^{-1}(\beta_{i,j}) U(\beta_{i,j}) \tag{3-15}$$

Let starting values be $\beta_{i,0}$, and substitute it into the right hand side of equation 3-15, which yields the result for the first iteration $\beta_{i,1}$. These values are then substituted back into the right-hand side, the first and second derivatives are recomputed, and the result is $\beta_{i,2}$. This process is repeated until the maximum change in each parameter estimate from one step to the next is less than some criterion. After the solution $\hat{\beta}_i$ is found, a byproduct of the Newton-Raphson algorithm is an estimate of the covariance matrix of the coefficients, which is just $-I^{-1}(\hat{\beta}_i)$.

3.2.4 Analysis of model fit

The slope coefficient β_i associated with an explanatory variable x_i represents the change in log odds for an increase of one unit in x_i.

The likelihood ratio (L.R.) test for overall significance of the beta's coefficients for the independent variables in the model is used. The test based on the statistic L.R. under the null hypothesis that the beta's coefficients for the covariates in the model are equal to zero. L.R. statistic takes the form:

$$L.R. = -2\ln\left(\frac{L_{m2}}{L_{m1}}\right) \qquad (3\text{-}16)$$

where L_{m2} is the likelihood without the variable, and L_{m1} is the likelihood with the variable. The distribution of L.R. is a chi-square with q degree-of-freedom, where q is the number of covariates in the logistic regression equation.

The likelihood statistic L is used to assess the fitness of the model. The sampling distribution of the $-2lnL$ has a chi-square distribution with q degrees of freedom under the null hypothesis that all regression coefficients of the model are zero (Fienberg, 1980). A significant p-value provides evidence that at least one of the regression coefficients for an explanatory variable is non zero.

Hosmer and Lemeshow (2000) developed a goodness-of-fit test for logistic regression models with binary responses. They proposed grouping based on the value of the estimated probabilities. This test is obtained by calculating the Pearson chi-square statistic from the 2×g table of observed and expected frequencies, where G is the number of groups. The statistic is written

$$HL = \sum_{g=1}^{G} \frac{(y_g - n_g\hat{p}_g)}{n_g\hat{p}_g(1-\hat{p}_g)} \qquad (3\text{-}17)$$

where: n_g is the number of observation in the g^{th} group, y_g is the number of event outcomes in the g^{th} group, $\hat{p}_g$ is the average estimated probability of an event outcome for the g^{th} group.

The HL statistic is then compared to a chi-square distribution with $(g - 2)$ degree of freedom.

3.3 Bayesian Network

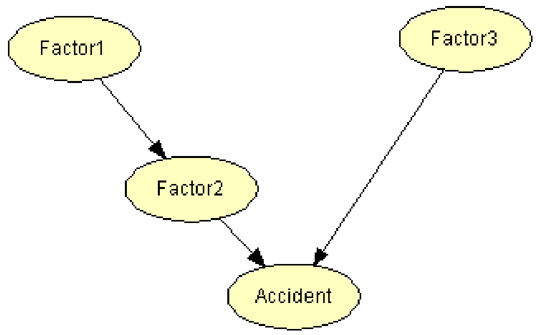
How the various factors simultaneously affected the vessel safety level were studies. In addition, A Bayesian Network (BN) approach has been developed to model the effect of shipowners' efforts by taking into account different influencing factors and their mutual influences.

3.3.1 Definitions

A BN is a probabilistic graphical model that represents a set of random variables and their conditional independencies in a directed acyclic graph (DAG). The DAG consists of a set of nodes representing variables and edges representing the probabilistic causal dependence among the variables.

A variable which is dependent on other variables is often referred to as a child node, which contains a conditional probability table (CPT). Directly preceding variables are called parents nodes, which contains marginal probability table. There is an edge from factor1 to another node factor2, then factor1 is called parent of factor2 (Figure 3-3)

Figure 3-3: Sample of Bayesian Network



The causal dependence between variables is expressed by the structure of nodes, which gives the qualitative part of causal reasoning in a BN. The relationship between variables and the corresponding states are given in a conditional probabilistic table (CPT) attached to each node, which constructs the quantitative part.

3.3.2 Bayes's theorem

A Bayesian Network is a representation of the joint probability distribution of the entire variable domain.

3.3.2.1 Joint Probability Distribution (JPD)

Suppose that the safety control system X is affected by two factors. Let A be the number in the first factors and let B be the number in the second factor. Then the joint event $A \text{ and } B$ is the overall number of factors in the system. The probability of this event is$P(A,B)$, which is the joint probability distribution of A and B. $P(A,B)$ is the set of probabilities $\{P(a_i,b_j)|i=1,\cdots,n;j=1,\cdots,m\}$. $\{a_1,a_2,\cdots a_n\}$ and $\{b_1,b_2,\cdots b_m\}$ are the possible states sets of A and B.

Once a JPD has been defined, and then base on the marginalization rule, any probabilistic query regarding any of the variables could be calculated. $P(A)$ can be calculated if the joint probability distribution$P(A,B)$ is know.

$$P(A)=\sum_i P(A,b_i) \tag{3-18}$$

In general, a probabilistic model may consist of a set of variables $X=\{X_1,X_2,\cdots,X_n\}$, which exploits conditional independence to represent the JPD over X having the product form (Pearl, 1988):

$$\begin{aligned} P(X_1,\cdots X_n) &= P(X_1|X_2,\cdots,X_n)P(X_2,\cdots,X_n) \\ &= P(X_1|X_2,\cdots,X_n)\,P(X_2|X_3,\cdots,X_n)P(X_3,\cdots,X_n) \\ &= P(X_1|X_2,\cdots,X_n)\,P(X_2|X_3,\cdots,X_n)\cdots P(X_{n-1}|X_n)\,P(X_n) \\ &= P\big(X_1|parent(X_1)\big)\cdots P\big(X_n|parent(X_n)\big) \\ &= \textstyle\prod_{i=1}^{n} P(X_i|parent(X_i)) \end{aligned} \tag{3-19}$$

Where $P(X_1,\cdots X_n)$ is the joint distribution of X to X_n and $P(X_1|X_2,\cdots,X_n)$ is the conditional distribution of X_1 given $X_2,\cdots,X_n$, where the given information $X_2,\cdots,X_n$ is called the parent variables X_i.

The space, and consequently, time complexity required in representing and manipulating the JPD is exponential in the number of variables considered (D'Ambrosio, 1999). For example, the JPD required to represent a system with 10 binary values would have 2^{10} (1024) values. This causes a problem in the elicitation, storage, and manipulation of these values, thus making the use of JPDs unfeasible for any practical use.

3.3.2.2 Conditional Probability

The basic expressions about probability in the Bayesian approach are statements about conditional probabilities. In general $P(A|B)$ represent a belief in A under the assumption that B is known. And the conditional probability is defined via joint probabilities.

$$P(A|B) = \frac{P(A,B)}{P(B)} \tag{3-20}$$

3.3.2.3 Bayesian rule

The principles behind BN are Bayesian statistics and concentrate on how probabilities are affected by both prior and posterior knowledge. So the BN analysis begins with providing initial or prior probability estimates for specific outcomes or events of interest. Then from sources such as a database, a case study, etc., some additional information (i.e., data or evidence) about the event is obtained, which provides new data belief. The prior probability values are updated by calculating revised probabilities, which are posterior probabilities.

Bayes's rule provides a means for making these probability calculations. Given for two events, A and$B$, event B with states$\{b_1, \cdots\ b_m\}$, essentially, it is a relationship between conditional and marginal probabilities can be expressed as:

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \qquad (3\text{-}21)$$

which is the so-called Bayes Rule or Bayes Theorem. Where, $P(A)$ is called the prior probability of A; $P(A|B)$ is called the conditional or posterior probability of$A$, given$B$; $P(B)$ is the prior or marginal (total) probability of$B$, $P(B|A)$, for a specific value of B, is called the likelihood function for A, given B and can also be written as $L(A|B)$.

Generally, for an event B with states, the posterior probability on the event A can be computed from the Bayes's rule as

$$P(A|B) = \frac{P(B|A)P(A)}{\sum P(B|A_i)P(A_i)} \qquad (3\text{-}22)$$

Such a rule is especially significant for BNs, because it provides a means of calculating the full JPD from conditional probabilities, which is what a BN stores. For example, three events A, B, and C, can be expressed more compactly as:

$$P(A,B,C) = P(A|B,C)P(B,C) = P(A|B,C)P(B|C)P(C) \qquad (3\text{-}23)$$

Then, in applying Equation (3-24), Bayes's theorem specifies the probability of an eventA, given the condition that an event B and an event C both occur $(B \rightarrow A \leftarrow C)$ as:

$$P(A|B,C) = \frac{P(B|A,C)P(A|C)}{P(B|C)} \qquad (3\text{-}24)$$

3.3.2.4 Inference

One of the main advantages of BNs is that they allow inference based on observed evidence. The model is updated in accordance with observations using Bayesian rule. For the random variables A and B, Bayes's rule states:

$$P(A|B) = \frac{P(B|A)P(A)}{\sum P(B|A_i)P(A_i)} \tag{3-25}$$

Assume for instance that B is observed to be in states b_j. By applying equation (3-26) to each state of A, the proabability distribution $P(A|B = b_j$is computed:

$$P(A|B = b_j) = \frac{P(B=b_j|A)P(A)}{\sum P(B=b_j|A_i)P(A_i)} \tag{3-26}$$

3.3.2.5 The marginalization rule

Marginalization of a parameter in a system may be necessary if a probability table is given in which P_1 is dependent on anther, and the probability for the independent parameter is not provided.

$$P(B = \mathrm{b}_j) = \sum_i^m P(A = a_i)P(B = b_j|A = a_i) \tag{3-27}$$

The accident probability model is based on the notion of conditional probability, conditioning on the factors that determine the level of accident potential in a situation. To estimate the probability of an accident, the possible situations were sum over giving

$$P(A) = \sum_{j=1}^{k} P(A|S_j)P(S_j) \quad (3\text{-}28)$$

where S_j denotes the possible combinations of values of the factors for $j = 1, \ldots, k$ and k is the total number of possible combinations. $P(S_j)$ is the probability that particular combination of values of the factors occurs in the system. $P(A|S_j)$ is the probability that an accident occurs in the defined situation.

One can incorporate new node(s) as the data become available. Owing to this additional capability of a BN model, it can constitute a description of the probabilistic relationships among the system's variables that amount to a factorization of the joint distribution of all variables into a series of marginal and conditional distributions. Evidence propagation may take place via a message posting scheme.

3.3.3 Influence diagram

An influence diagram (ID) is a BN augmented utility functions and variables representing decisions. ID is a formal tool for modeling decision processes and computing optimal strategies under risk. For making the best possible decisions, the utilities were associated with the state of ID. These utilities are represented by utility nodes. Each utility node has a utility function.

Making decisions influences the probabilities of the network and the algorithms for probability updating can be modified to solving IDs. Its evaluation is done by setting the value of the decision node to a particular choice of action, and treating the node just as a nature node with a known value that can further influence the values of other nodes.

Firstly, calculating the conditional probabilities for the parents of the utility node and then feeding the results to the utility function, the actions utility can get. The expected utility (EU) of each decision alternative can be computed.

A utility table $U(D,S)$ is needed to yield the utility for each configuration of decision alternative and outcome state for the determining variable. The EU of a given decision alternative d is calculated by

$$EU(D) = \sum_S P(S|d)U(d,S) \tag{3-29}$$

where $U(d,S)$ are the entries of the utility table in the value node U. The conditional probability $P(S|d)$ is computed from CPT of the determining variable having outcome states, $s \in S$, given that the decision alternative d is fired.

The alternative with the highest EU is chosen; this is known as the maximum expected utility (MEU) principle. This implies that a rational decision maker should choose an action that maximizes EU of outcome states. Thus, given that $d_1, d_2, \cdots d_m$are the mutually exclusive decision alternatives of$D$, the decision alternative d that gives MEU is:

$$MEU(d) = \max_d\{EU(d_1), EU(d_2), \cdots, EU(d_m)\} \tag{3-30}$$

Utility theory can be used in both decision making under risk (where the probabilities are explicitly given) and in decision making under uncertainty (where the probabilities are not explicitly given). The theory can be expanded to application for safety based marine and offshore decisions through cost benefit evaluation, whereby utmost considerations, for cost-effectiveness, are given to both cost and safety (i.e., risk reduction).

3.3.4 Proposed BN methodology

A BN reasoning process has been developed to provide a natural framework for maritime risk assessment and decision support. A flow chart of the approach is shown in Figure, and the entire methodology consists of eight key steps. And explanations for each of the steps are given as follows:

Step 1—Gather Available Accident Category Information

It is vital to the BN process is gather available information and accident data collected from every possible source. All the accident information can be used to identify the influencing factors relating to the accident. The data may come from accident report, databases and networks, tests and analytical models. Expert judgment is utilized throughout the understanding of the domain and also in assigning valuable figures where data are not available. As observed data becomes available, they can be used to update, refine, or replace the estimates provided by subject matter experts.

Step 2—Creation of Nodes with Dependencies

The constructing of a Bayesian Network begins with the graphical representation of the nodes and their dependencies (that is, the structure). The structure may be defined using prior information, by means of an estimate made from the data or a combination of the two.

The influencing nodes relating to the maritime accident can be mapped as labeled nodes into the network pane. Identified influence relationships between nodes are established such that an arc connection is placed between a parent node and a child node.

Step 3—Create CPTs and Prior Probabilities

Having established the influencing nodes together with the dependencies, a conditional probabilistic table can be developed for each node or event. Nodes without any parents give probabilities that are marginal probabilities.

Theoretically, the CPT may be populated using historical evidence, expert judgments or a combination of the two.

In this research, a binary logistic regression method is used to provide the conditional probability (P) of a ship involved in a casualty. The binary logistic model provides the necessary coefficient (β) in order to compute the estimated probability of casualty given a certain combination of conditions (dependent variables X).

Step 4—Normalise of Probability Values in the CPT

The probability of the marginal and conditional terms should be nonzero, and between 0 and 1. Thus, the process in this step is to normalize the probability values in every column of CPTs and becomes 1 after normalization.

Step 5—Propagation of Evidence

Through the propagation of the model, results are established. It is should keep in mind that entered evidence propagates in both directions, even though the graph is directed.

Step 6—Generate Posterior Probabilities

Once the structure and parameters have been determined from the data, the Bayesian Network is ready to draw inferences.

The beliefs computed after evidence is entered to improve the state of knowledge, and thus the prior probability values, are updated by calculating revised probabilities, which is the posterior probabilities $P(A|B)$. Posterior marginal probabilities, $P(A)$ and $P(B)$, can be obtained by use the marginalization process.

Step 7—Creation of Decision Node(s) and Utility Node(s)

An ID should be constructed so that one can see exactly which variables are known at the point of deciding for each decision node. A decision node must link to a chance node, which state is known at the time of making a decision. This is only one directed path from a chance node to a decision node.

Evaluation of the ID is done by setting the value of the decision node to a particular choice of action, and treating the node just as a nature node with a known value that can further influence the values of other nodes.

The conditional probabilities for the parents of the utility node should be calculated firstly using the standard inference algorithm, and then feeding the results to the utility function. The utility figures can be given in terms of property, health, finances, liability, people, environment, public confidence, etc. When propagating, one can follow the maximum expected utility principle, the decision with the highest of decision should be choosing.

Step 8—Validation of the model

Model validation is the essential part of the model development process if models to be accepted and used to support decision making. In this study a sensitivity analysis for partial validation of the model is developed, the following two axioms must therefore be satisfied:

Axiom 1. A slight increase/decrease in the prior subjective probabilities of each parent node should certainly result in the effect of a relative increase/decrease of the posterior probabilities of the child node.

Axiom 2. The total influence magnitudes of the combination of the probability variations from x attributes (evidence) on the values should be always greater than the one from the set of x-y ($y \in x$) attributes (sub-evidence).

3.4 Bi-matrix games

3.4.1 Definitions of Bi-matrix games

A $m \times n$ bi-matrix game is represented by two $m \times n$ payoff matrices A and B, where the entries A_{ij} and B_{ij} denote the payoffs for player I and player II in the i-th row and j-th column of A and B. The payoffs can be considered as a profit or loss for the players. It is considered as cost in this research.

The mixed strategy for player I is a probabilistic decision vector $x \in \mathbb{R}^M$, where $x \geq 0$ and $1^T x = 1$. The mixed strategy for player II is a probabilistic decision vector $y \in \mathbb{R}^M$, where $y \geq 0$ and $1^T y = 1$. Denote X and Y as the set of mixed strategies for player I and II.

Nash (1951) introduced the notion of equilibria for N-person non-zero sum games, and showed the existence of equilibrium by using Brouwer's fixed point theorem. A pair of mixed strategies $(\bar{x}, \bar{y}) \in X \times Y$ is said to be at the Nash equilibrium point if

$$\bar{x}^T A \bar{y} \geq x^T A \bar{y} \;\; for\ all\ \; x \in X$$

$$\bar{x}^T B \bar{y} \geq x^T B \bar{y} \;\; for\ all\ \; y \in Y$$

In other words, a Nash equilibrium point is a pair of strategies that do not motivate any one of the players to change his strategy as long as the other stays with his strategy.

3.4.2 A theoretical model for strategic maritime inspection

The essential ingredients of the theoretical framework to be introduced below consist of three parties. A regulator represents the legal port authority that imposes regulatory constraints on both the PRC programs and shipowners. The shipowners and the controllers of the port implement the directives as they are set by the port regulators. Assume then that the controllers have a choice of m inspection control strategies, while shipowners have a set of m strategies they can turn to meet the port regulatory constraints and thereby prevent potential accidents. Each shipowner is, of course, defined in terms of characteristics (size, ship age, etc.) that are known by the controller.

The game between the shipowner and the port authority can be expressed as that the shipowner is convicted and pays a fine when it is observed by the authority. The shipowner is given greater or lesser incentives to prevent pollution by the extent of the authority's investment in monitoring. The authority is aware of that. They behave strategically and try to optimize the design of inspections.

In this game, the port authority optimizes social welfare as the chief target (Florens and Foucher, 1999), but at the same time the inspection costs should also be taken into account. When an accident happens, there will be some pollution damage and cleanup or recovery costs. In this case, the damage and restoration costs can reflect social welfare losses. The government should consider these losses as a part of its costs.

There are, of course, additional cost consequences that are random, these expressing the costs of control (on both the controller and the shipowner), and the penalties in case a shipowner is found not to be complying with some of the regulations imposed etc. For convenience, these costs are defined by the random bi-matrix given as: $(\tilde{A}_{ij}, \tilde{B}_{ij})$. In other words, the controller and the shipowner are confronted by a bi-matrix random payoff game where the regulator determines the set of risks and other constraints, specified by $(\bar{\alpha}, \bar{\beta})$.

The resulting problem consists, then, in finding a solution to the random payoff (costs) game below.

$$Min\ Min\ (\tilde{A}, \tilde{B})$$

$$s.t. \sum_{j=1}^{m} \sum_{i=1}^{n} x_i y_i \alpha_{ij} \leq \bar{\alpha}$$

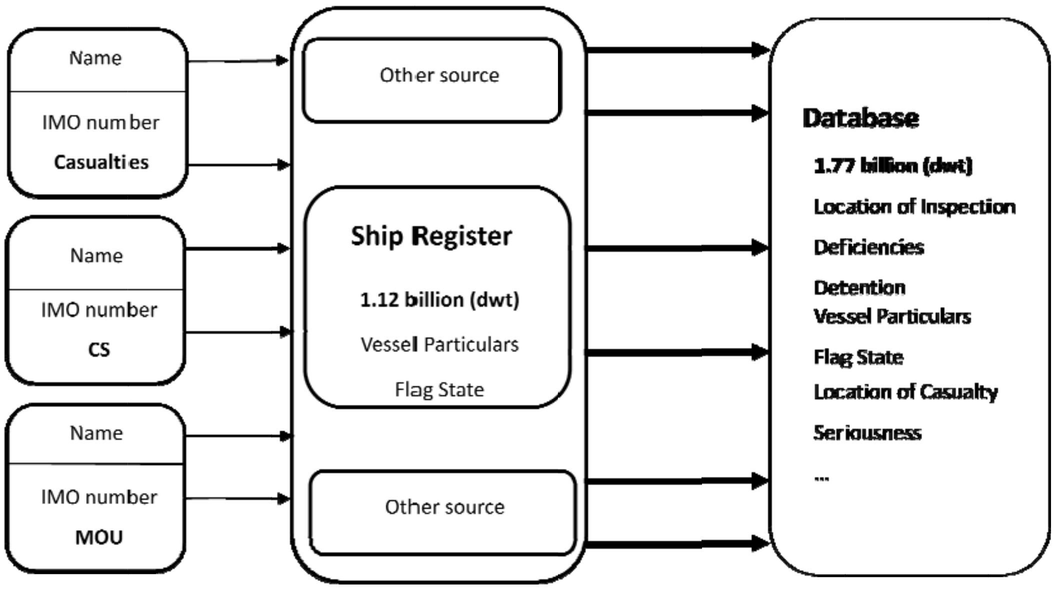
$$\sum_{j=1}^{m} \sum_{i=1}^{n} x_i y_i \beta_{ij} \leq \bar{\beta}$$

This general and theoretical framework provides an approach that can be used in dealing with specific port inspection problems, exhibiting the characteristics stated above, namely, being regulatory-risk constraints oriented, with an authority exercising control, and with shipowners.

Chapter 4：Database and variable preparation

A total dataset was built for this analysis. The shipping dataset is a combination of four individual datasets and when aggregated, it accounts for approx 140,000 ships. This datasets included approximation of the total ships whatever in existence or total lost (Figure 4-1).

Figure 4-1: Overview of database



4.1 The source of the database

There is a large volume of shipping data failed to be summarized and analyzed fully and systematically. This data exists in various forms, such as news, authority reports. The data can be categorized into two types – static and dynamic data. Static data include: the ship's name, code, date and place of building, and type and design. This information does not change during the life of a ship. Dynamic data refers to information relating to the management of the ships, including their registers, managers, insurers, crew, maintenance, accidents, detentions, surveys, claims, trade patterns, and types of cargo loaded.

This database not only included the static data, but also the dynamic data. The static data mainly comes from PC registers (Lloyd's Register, London), which is a powerful database describes each vessel with over 200 variables such as vessel flag, date of building, vessel tonnage.

Dynamic data exists in various sources, including news reports and government reports. Port State Control (PSC) inspection reports are important data source for the dynamic data. PSC is the inspection of foreign ships in national ports to verify that the condition of the ship and its equipment comply with the requirements of international regulations and that the ship is manned and operated in compliance with these rules. One inspection report will be published in the internet when the inspection finished. This report included the list of deficiencies and whether is detention or not. However, the sources are mostly in free text form, and thus are not ready to undergo a statistical analysis without pre-processing to transform the data into a presentable form. A computer programming was made to collect this data and transform to a table.

Inspections database consists of 319623 inspection report from three main Memoranda of Understanding (MoU) for the time period January 2000 to 2008 (Table 4-1).

Table 4-1: Inspections database

Source	Time	Records	Number of Vessels	Total
Tokyo MOU	2000.01.01--2008.12.31	205418	22923	
Paris MOU	2005.01.01--2008.12.31	75631	20286	36369
India MOU	2002.01.01--2008.12.31	38574	12622	

The casualty dataset that consists of 7966 records for time period 1993-2008 and is a combination of data received from World casualty statistics and the International Maritime Organization (IMO). *World Casualty Statistics* (WCS), which published by *Lloyd's* Register of Shipping, consists of 2624 casualty's records for time period 1993 to 2008. The website of IMO provides 6864 casualty's records which collected from reports of investigations into casualties received at IMO.

IACS Procedural Requirements require member societies to provide monthly reports on ships in class; class suspensions lasting more than 7 days, reinstatements, withdrawals and reassignments; transfers; and ISM Code and ISPS Code certificates issued (IACS, 2010).

This information is collected directly by Equasis and is available from the website of IACS. Around 40000 ships included in this dataset, which including: IMO, Ship Name, Class, Date of Survey, Date of Next Survey, Date of Latest Status, Status Code and Reason for Status.

The relationship of this four datasets are, if the casualties report including the IMO number and the number could be found in the PC registers, then combined the two datasets and put into the final dataset. If the report does not have the IMO number, then search the vessel name from the PC registers and reconfirm by the vessel particulars, such as date of building, ship type and so on. If all of them could be match, then this report put into the final dataset.

If vessel does not including in the PC registers, then search this ship from other source to complete the record and put into the final dataset.

So the final shipping dataset include almost all the vessels whatever in existence or total lost already.

4.2 Overview of database

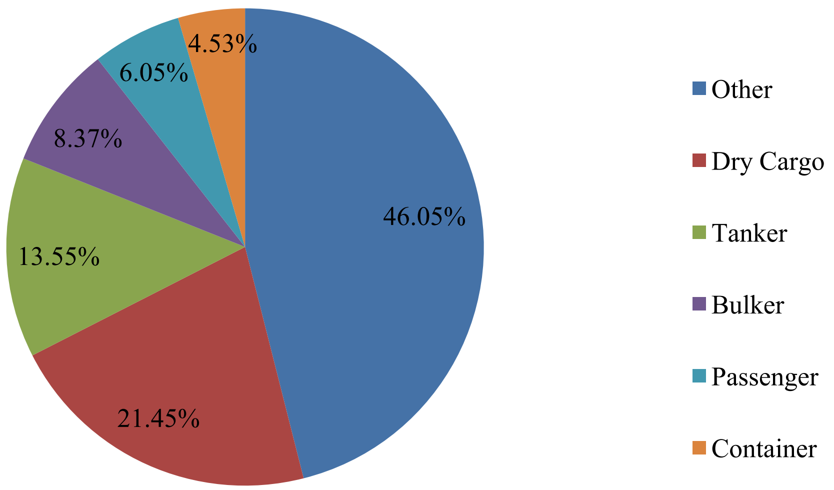
4.2.1 Vessel type

Vessel type determines the vessel's function in seaborne transportation, and principally affects the possibility of a certain vessel potentially suffering a particular type of maritime peril.

The selection of vessel types for the analyses is important. According to the Lloyd's list (Lloyd's Fairplay, 1993-2008), all vessels were separated into general cargo & multipurpose, bulk, container, tanker, passenger vessel and others. Table A-1 listed the ship types have been aggregated out of the original ship types in details.

Figure 4-2 then gives an overview of the split up of the vessel types. Due to have the most sub classification, Dry cargo and tanker are the world's two largest vessels type in terms of number. There are 26645 dry cargo ships and 16830 tankers of 100 GT and above. These two types of ships represented 35 % of total vessels. Container ship is the smallest vessels type. There are 5646 container ships of 100 GT and above, which represented 4.53% of total vessels. About 46.06% of the total vessels belong to others, which included the fishing vessels, offshore and miscellaneous vessels.

Figure 4-2: Overview of the vessel types



4.2.2 Classification Societies (CS)

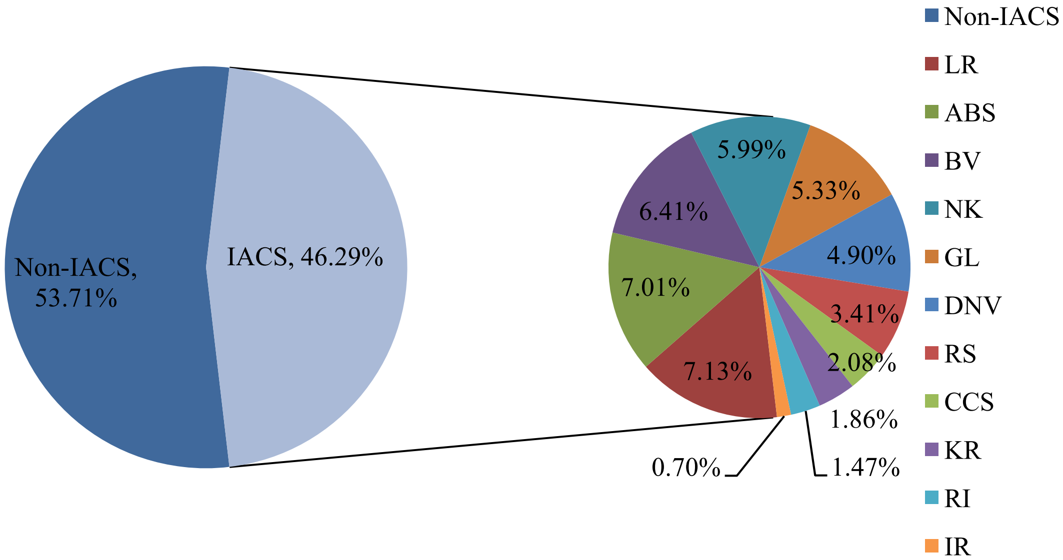
A classification society is a non-profit organization that sets rules and technical standards for the quality and integrity of vessels, and performs surveys to determine whether vessels are in compliance with the classification society's rules and regulations, national laws and international conventions (Clark, 2009). Without being certified by a classification society vessels cannot operate, since classification is an absolute prerequisite for vessel registration and insurance cover (Clark, 1991). There are currently approximately 50 classification societies that provide maritime classification services, some of which are recognized within the industry to be of a better quality and standard than others. The International Association of Classification Societies (IACS) consists of 10 member societies.

1) American Bureau of Shipping (ABS)
2) Bureau Veritas (BV)
3) China Classification Society (CCS)
4) Det Norske Veritas (DNV)
5) Germanischer Lloyd (GL)
6) Indian Register Of Shipping (IRS)
7) Korean Register of Shipping (KRS)
8) Lloyd's Register (LR)
9) Nippon Kaiji Kyokai (NK)
10) Registro Italiano Navale (RINA)
11) Russian Maritime Register of Shipping (RS)

As regards the number of ships (Figure 4-3), the IACS account for over 46% of the entire world fleet. LR, ABS and the BV are the worlds three largest CS in terms of number .These three organizations registered 25533 ships of 100 GT and above. LR dominates the scene with over 8856 ships accounting for over 7% of the world vessels.

At the eleventh position, IRS, which has been admitted as a full member of the IACS in 2010, registered 866 ships (0.7% of world ships).

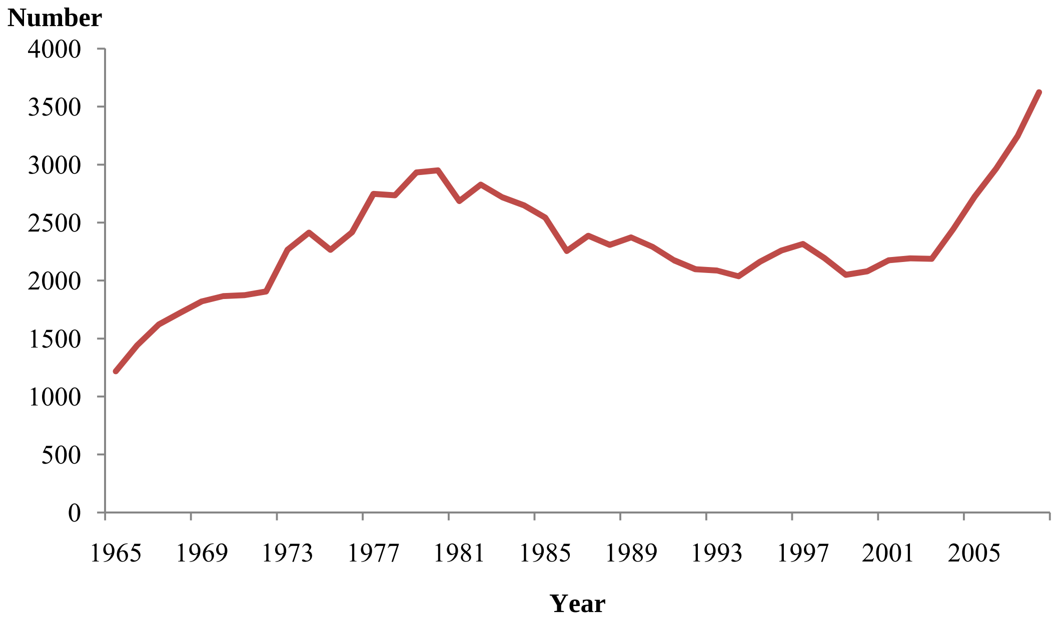
Figure 4-3: Overview of the classification society



4.2.3 Delivery of new buildings every year

With the great increase in international trade, the demand for the seaborne transportation has been growing at an unprecedented speed. Accordingly, the expansion of the world trading vessels has been the evidence of the growing maritime transport (Figure 4-4). Especially from 1965 to 1980, the deliveries of new buildings ships had a significant increase each year. The average growth rate of deliver new ships is almost 6.3% during the 15 years. After 1980, the growth rates became relative stable, but the number of deliver still remained in the higher level over, that is 2000 ships were delivered each year. From 2003, the average growth rate of deliver new ships is over 10%. Even in spite of the global economic crisis, the world's shipyards delivered 3623 ships in 2008.

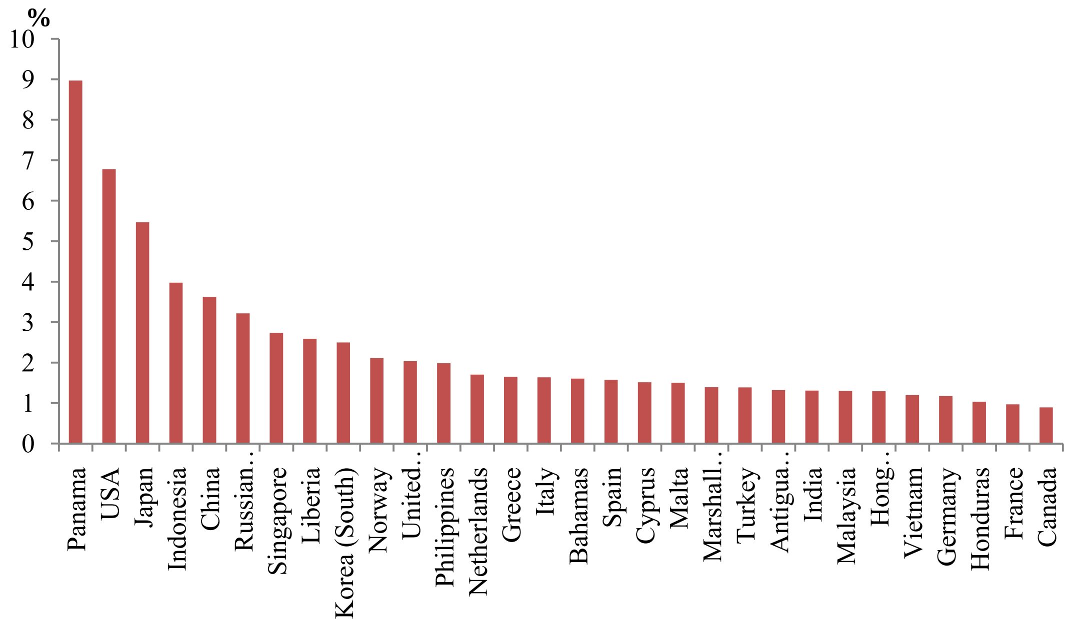
Figure 4-4: New buildings every year



4.2.4 Flag states

As regards the number of ships (Figure 4-5), the 30 countries and territories with the largest vessels registered under their flag account for 70.43 % of the world vessels. The largest flag of registration is Panama (11142), 8.97% of the world vessels, followed by United State (8423), 6.78% of the world vessels.

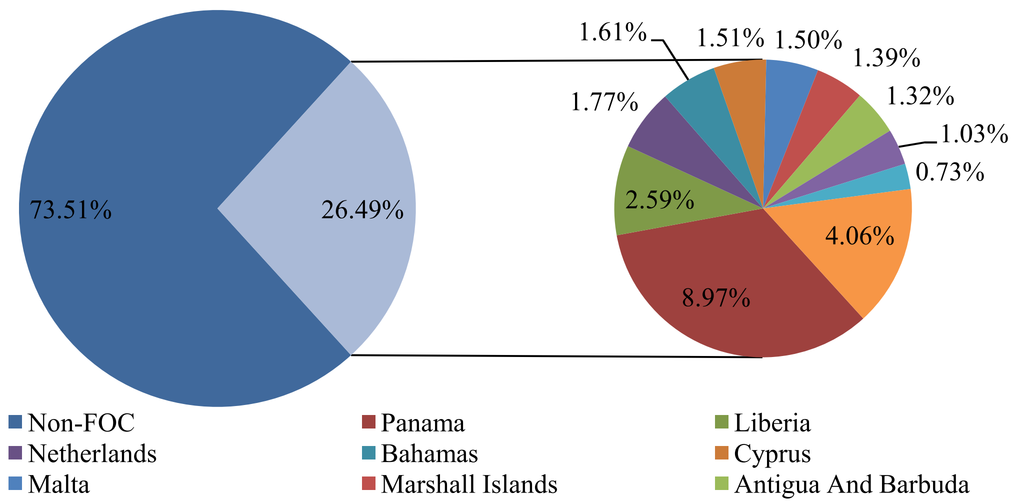
Figure 4-5: Overview of the flag state



The International Transport Workers' Federation maintains a list of 32 registries it considers to be Flags Of Convenience (FOC) registries. As of 2010 the list includes Antigua and Barbuda, the Bahamas, Barbados, Belize, Bermuda, Bolivia, Burma, Cambodia, the Cayman Island, Comoros, Cyprus, Equatorial Guinea, Georgia, Gibraltar, Honduras, Jamaica, Lebanon, Liberia, Malta, the Marshall Islands, Mauritius, Mongolia, Netherlands Antilles, North Korea, Panama, Sao Tome and Príncipe, St Vincent, Sri Lanka, Tonga, Vanuatu, and the French and German International Ship Registers.

Panama, Liberia and the Netherlands Antilles are the world's three largest registries in terms of number (Figure 4-5).These three organizations registered 16561 ships of 100 GT and above. Panama dominates the scene with over 11142 ships accounting for almost 9% of the world vessels.

Figure 4-5: Overview of the FOC



4.3 Descriptive statistics and key figures for casualties

The casualty database consists of 7966 records which combines WCS and the report from IMO1. Accord to casualty first events, the casualty main include: foundered, fire/explosion, wrecked/stranded, grounded, collision, contact and others. Ships attacked by pirates and ships lost due to war were can not control by shipowner or the government, which were not including in this research. Those incompletely reports, which main variables cannot be supplemental through other source, were deleting from this database. Finally, 6888 cases were remained.

[1] LMIU(Lloyds Maritime Intelligence Unit) and MAIB(Marine Accident Investigation Branch) were considered at first. But the detail information of accident cannot be obtained from the data source. Compared with previous research which used these two databases, there is no significant difference from the one in this research. Nevertheless, the database will be completed in the future work.

4.3.1 Seriousness of casualties

According to IMO Circular 953, ship casualties are classified as “very serious casualties” “serious casualties” “less serious casualties” and “marine incidents”. Administrations are requested to submit data for marine incidents, which was eliminated in this research.

Very serious casualties are casualties to ships which involve total loss of the ship, loss of life or severe pollution. The “Severe pollution” is a case of pollution which, as evaluated by the coastal State(s) affected or the flag State, as appropriate, produces a major deleterious effect upon the environment, or which would have produced such an effect without preventive action.

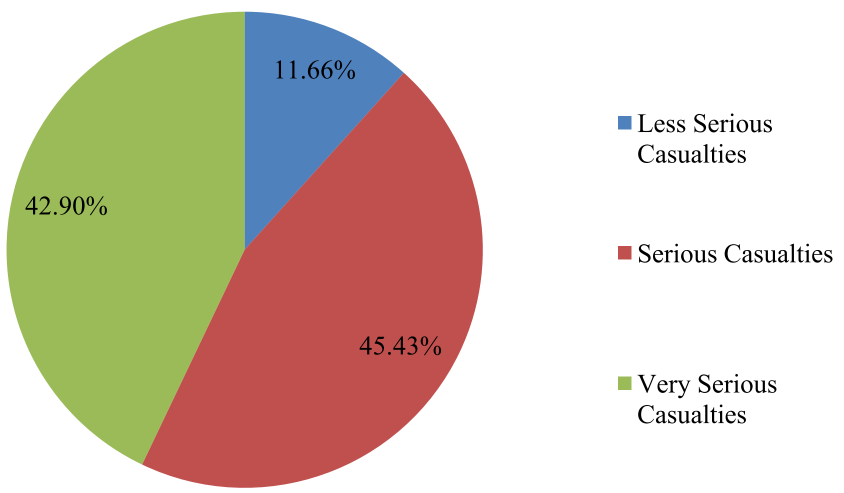
Serious casualties are casualties to ships which do not qualify as “very serious casualties” and which involve fire, explosion, collision, grounding, contact, heavy weather damage, ice damage, hull cracking, or suspected hull defect, etc. The result main include:

1) Immobilization of main engines, extensive accommodation damage, severe structural damage, such as penetration of the hull under water, etc. rendering the ship unfit to proceed,
2) Pollution (regardless of quantity)
3) Breakdown necessitation towage or shore assistance.

Less serious casualties are casualties to ships which do not qualify as “very serious casualties” or “serious casualties” and for the purpose of recording useful information also include “marine incidents” which themselves include “hazardous incidents” and “near misses”.

Figure4-6 gives an overview of the classification of the casualty type. The figure show that serious casualties have larger percentages, over 45%, following is the very serious casualties, almost 43%. Less serious casualties only have 11.66%, which does not means the less serious casualties occurred less. The reason is most of the less serious casualties were not report to the administration.

Figure 4-6: Classification of seriousness of casualties

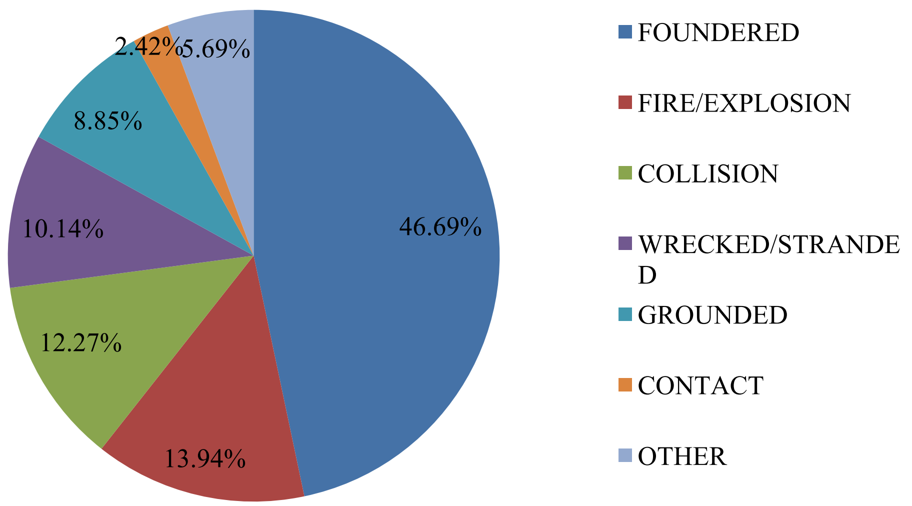


4.3.2 Type of casualties

In addition to the classification of seriousness of casualties, the cases were also examined and re-classified according to casualty first events. The casualty first events are classified as follows: foundered, fire/explosion, wrecked/stranded, grounded, collision, contact and others.

Figure4-7 shows the percentage of casualties by the casualty first events. The figure show that foundered has larger percentages, almost 47%, followed by the fire/explosion at almost 43%. Collision, wrecked/stranded and grounded accounting for 12.27%, 10.14% and 8.85% separately. Contact only accounting for 2.42%.

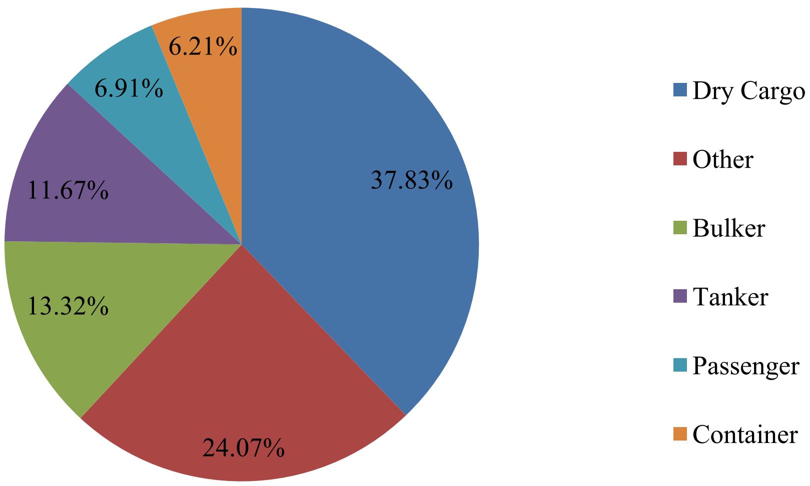
Figure 4-7: Type of casualties



4.3.1 Casualties for different vessel types

Figure 4-8 shows the frequency of casualties' occurrence for the six vessel types used in this analysis. Attribute 38% of the casualties to dry cargo ship. Bulker and tanker have similar percentage (13.32% and 11.67% respectively). Passenger and container have lower percentages (6.91% and 6.21% respectively). At the second position, the "other" category of vessel type accounting for over 24%. These high occurrence rates for these vessel types clearly identify them for further analysis.

Figure 4-8: Casualties of different vessel types



4.3.2 Age distribution of casualties

Figure 4-9 shows that 23.12% of casualties' vessel less than 10 years old, around 61.7% between 11 and 30 years old and 15.18% more than 30 years old. The mean age of vessels at casualties is about 19.8 years.

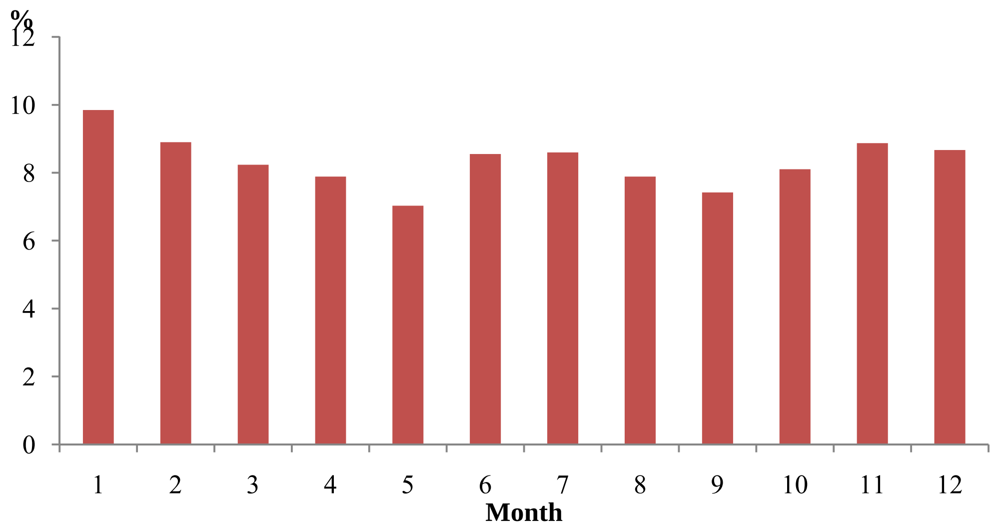
Figure 4-9: Age distribution of casualties

4.3.3 Casualties in each month

Different seasons generate different weather conditions. So the probability of accident is different when the vessel is sailing in a different season. The accident season can be derived from the recorded month in which the maritime accident occurred.

Figure 4-10 shows that the numbers of casualties do not have significant difference for the different month. The most casualties occurred in January (9.85%). The lowest is May (7.03%).

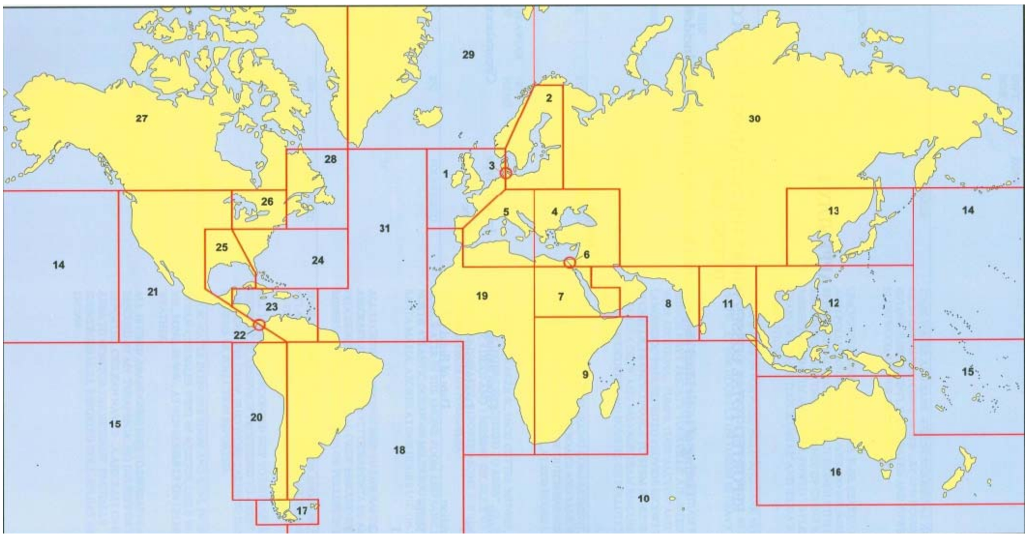
Figure 4-10: Casualties in each month



4.3.4 Casualties in each zone

In accordance with the world casualty statistics, the whole of the world's ocean region has been divided into 31 zones (see Figure 4-11). Due to their unique geographical environment, different regions will have different effects on a vessel's safety.

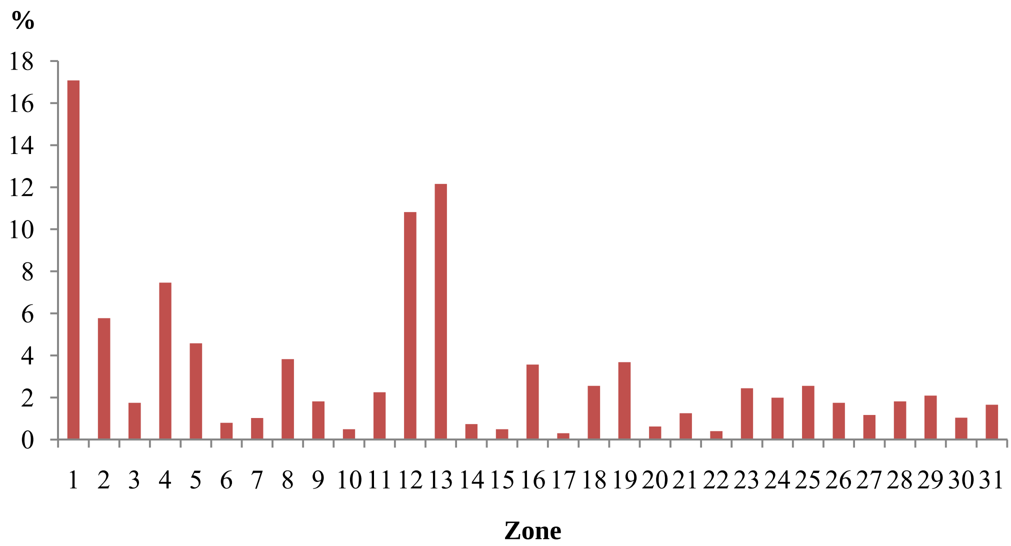
Figure 4-11: World map showing zones



Source: World Casualty Statistics (2008)

Figure 4-11 shows that the most danger zone is the 1, which refer to the areas around the UK. About 17.07% casualties happed in this area. Secondly is the zone 13, where is the eastern Asian countries, such as China, Japan and Korea. About 12.15% casualties happed in this area. Southern China Sea (zone 12) is the thirdly danger area, about 10.82% casualties happed in this here. The Mediterranean (zone 4 and 5), the Indian Ocean (zone 8) and the (zone 2) are all belong to more dangerous area.

Figure 4-12: Casualties in each zone

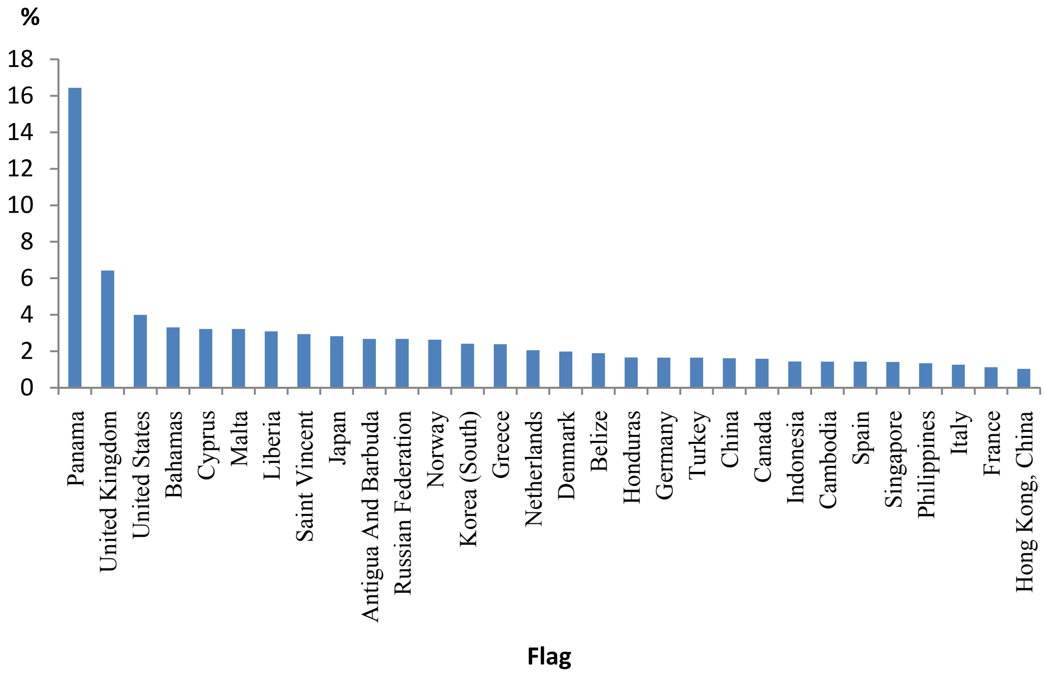


4.3.5 Casualties of different vessel flag

Figure 4-13 shows that the most causalities vessel flies the Panama flag (16.44%). The second on is the UK (6.42%). The vessels with the flag of Hong Kong, France and Italy have less causality.

Among the top 10 dangers countries, 7 belong to the flag of convenience country. Except Panama, they are Bahamas (3.31%), Cyprus (3.22%), Malta (3.22%), Liberia (3.09%), St.Vincente (2.94%), and Antigua and Barbuda (2.68).

Figure 4-13: Casualties of different vessel flag



The availability of suitable data necessary for each step of the FSA process is very important. Most of the time, such data is not available. Lack of reliable safety data is one of the major problems in marine safety analyses (Wang, 2001). Therefore, a comprehensive database was built for this analysis. The shipping dataset is a combination of four individual datasets, which when aggregated together accounts for approximately 140,000 ships.

Chapter 5：Risk indicator and estimation of probability

5.1 Estimation of the probability of accident

The probability of the accident is estimated based on a comparative evaluation process that examines performance measured by accident rates. The safety measures used to calculate a marine probability of an accident should ideally be risk-based. In this sense, the probability of the accident can be regarded as risk indicators. The probability of the accident can generate a relative risk score for each existing vessel, and it serves as a vessel safety benchmarking and management tool for various users. The result will continue to be improved, with dynamic information regarding updated vessel movements and management changes, as well as accurate inspection and survey reports.

5.1.1 Risk indicators and hypotheses

Risk cannot observe directly, but the probability of the occurrence of an accident can be measured through analysis historical data on safety indicators.

There are many variables and large numbers of observations in the database. If too many insignificant variables include in the model may result in the weak predictive power. Therefore, the variable selection is fundamental to build the model. The approaches that have been used in variable selection are diverse and plentiful (Austin and Tu, 2004; Wang et al., 2008). In this research, the stepwise backward elimination and prior knowledge are used. Firstly, through the literature review, as much as possible the candidate variables are collected, due to the connection with the probability of an accident. At the mean time, several hypotheses are defined. Secondly, the correlation tests are provided among all of the candidate variables. The significantly correlated variables are divided into the different candidate groups.

Backward elimination begins with a model consisting of all candidate variables. The insignificant variables are sequentially eliminated one by one from the model basing on the p-value. On the other hand, the information criteria, AIC (Akaike Information Criterion) and SC (Schwarz Criterion), are also calculated. If the two criteria indicate the lowest decreases of their values, the elimination of a certain variable is deemed to be reasonable. Finally, 205 variables are ascertained and listed in Table 5-1.

5.1.1.1 Internal variables

Indicator 1: Vessel age

Since vessel structural failure can be expected to increase with age, the a priori sign of the relationship between vessel age and its occurrence probability of an accident is positive. Cariou et al. (2008), through analysis of PSC observations, concluded that older and younger vessels were found to have less deficiencies, and the probability of belonging to the "always deficient" category is highest for vessels between 25 and 30. Approximately the same result was obtained by Li et al. (2009). Knapp and Franses (2007) found that vessel age only has a significant effect on very serious casualties and that the effect is positive.

Hypothesis 1: With an increase of vessel age, the probability of accident is increased.

Indicator 2: Vessel size

With its larger scale, a huge-size vessel will maybe have reduced maneuverability at sea, which thus increases the probability of an accident. But Knapp and Franses (2007) have shown that a smaller vessel seems to be at higher risk than a larger vessel for very serious casualties. The opposite result was obtained by Li et al. (2009) through analysis of total-loss incidents. They found that the probability of a total-loss incident increases with the vessel size. Jin et al. (2005) found that medium size fishing vessels have a higher accident probability compared with the largest vessels. So the relationship with respect to vessel size is unclear.

Hypothesis 2: With an increase in vessel size, the probability of accident increased.

Indicator 3: Vessel type

Vessel type determines the vessel's function in seaborne transportation, and principally affects the possibility of a certain vessel potentially suffering a particular type of maritime peril. According to the Lloyd's list (Lloyd's Fairplay, 1993-2008) all vessels were separated into general cargo & multipurpose, bulk, container, tanker, passenger vessel and others.

Cariou et al. (2008) identify passenger vessels as exhibiting more deficiencies in comparison to other vessel categories. However, Knapp and Franses (2007) have shown that general cargo vessels seem to carry the highest risk.

Hypothesis 3a: General cargo has an effect on the probability of accident.

Hypothesis 3b: Bulker has an effect on the probability of accident.

Hypothesis 3c: Container has an effect on the probability of accident.

Hypothesis 3d: Tanker has an effect on the probability of accident.

Hypothesis 3e: Passenger has an effect on the probability of accident.

Indicator 4: Classification Societies

A classification society is a non-profit organization that sets rules and technical standards for the quality and integrity of vessels, and performs surveys to determine whether vessels are in compliance with the classification society's rules and regulations, national laws and international conventions (Clark, 2009).

Knapp and Franses (2007) have shown that certain classification societies have a significant effect on the probability of casualties. So in the first model 34 dummy variables were used to find out which classification society has higher occurrence probability of an accident. In the second model one dummy variable were used to examine the effects of the IACS on maritime probability of an accident.

Hypothesis 4a: Different classification societies have a different effect on the probability of accident.

Hypothesis 4b: Compared with non-IACS members, the accident probability of vessels classified by IACS members is higher.

5.1.1.2 External variables

Indicator 5: Voyage zone

In accordance with the world casualty statistics, the whole of the world's ocean region has been divided into 31 zones (see Figure 4-11). Due to their unique geographical environment, different regions will have different effects on a vessel's occurrence probability of an accident. 30 dummy variables were used to control them.

Hypothesis 5: Zone of voyage affects a vessel's probability of accident.

Indicator 6: Vessel registry

Li (1999) found that open-registry vessels tend toward being substandard vessels, and the safety record of developing maritime countries as a group is better than that of already developed maritime countries, so two dummy variables were used to control the impact of such countries.

Hypothesis 6a: Different registry flags have a different effect on the probability of accident.

Hypothesis 6b: Compared with open registry vessels, closed registry vessels have a higher probability of accident.

Indicator 7: Time and season

The passing of time affects the controls for certain conditions - such as technological changes, regulations and congestion - that vary through time, but not across vessels. We expect these to indicate a generally declining trend in accidents through time, mirroring the substantial decline in aggregate accident rates over the period (Rose, 1990; Li et al., 2009). Different seasons generate different weather conditions. So the probability of accident is different when the vessel is sailing in a different season. The accident season can be derived from the recorded month in which the maritime accident occurred.

Hypothesis 7a: Time has an effect on the probability of accident.

Hypothesis 7b: The season of voyage has an effect on on the probability of accident.

Table 5-1: List of variables

Variables	Measurement	Variable type
Vessel characteristics		
X1	Vessel age in years	Continuous
X2	Vessel size in GT	Continuous
Vessel type		
X3	1 if a general cargo vessel, 0 otherwise	Dummy
X4	1 if a bulker vessel, 0 otherwise	Dummy
X5	1 if a container vessel, 0 otherwise	Dummy
X6	1 if a tanker vessel, 0 otherwise	Dummy
X7	1 if a passenger vessel, 0 otherwise	Dummy
Vessel classification		
X8	1 if vessel is classified by a member of the IACS, 0 otherwise	Dummy
X9	1 if vessel is classified by the American Bureau of Shipping, 0 otherwise	Dummy
X10	1 if vessel is classified by the Bureau Veritas, 0 otherwise	Dummy
X11	1 if vessel is classified by the China Classification Society, 0 otherwise	Dummy
X12	1 if vessel is classified by the Det Norske Veritas, 0 otherwise	Dummy
X13	1 if vessel is classified by the Germanischer Lloyd, 0 otherwise	Dummy
X14	1 if vessel is classified by the Korean Register of Shipping, 0 otherwise	Dummy
X15	1 if vessel is classified by the Lloyds Registry, 0 otherwise	Dummy

Table 5-1: List of variables (continual)

Variables	Measurement	Variable type
X16	1 if vessel is classified by the Nippon Kaiji Kyokai, 0 otherwise	Dummy
X17	1 if vessel is classified by the Registro Italian Navale, 0 otherwise	Dummy
X18	1 if vessel is classified by the Russian Maritime Register of Shipping, 0 otherwise	Dummy
X19-X39	Other Classification Societies	Dummy
Vessel Flag		
X40-X154	Flag state at the time of accident	Dummy
External variables		
X155-X184	1 if the incident occurred in the region i, 0 otherwise (i=1…30)	Dummy
X185	1 if a vessel operator's country is a developed country, 0 otherwise	Dummy
X186	1 if the country where the vessel's operator is domiciled is on open registry, 0 otherwise	Dummy
X187	1 for spring, 0 for otherwise	Dummy
X188	1 for summer, 0 for otherwise	Dummy
X189	1 for fall, 0 for otherwise	Dummy
X190-X205	Year (1993-2008)	Dummy

The variables listed in table 5-1 are a summary of the variables that are used in the regressions. The next two equations show the models used to estimate the vessel's safety level.

Model I $X\beta_i = \beta_0 + \sum_{i=1}^{7} \beta_i x_i + \sum_{i=9}^{184} \beta_i x_i + \sum_{i=185}^{255} \beta_i x_i$ (5-1)

Model II $X\beta_i = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \sum_{i=3}^{7} \beta_i x_i + \beta_8 x_8 + \sum_{j=185}^{255} \beta_j x_j$ (5-2)

We developed two separate model runs. In the first model, we tested which classification society has more safety and which flag has more safety. In the second model, we used three dummy variables to examine the effects of IACS, open registry and developed countries on maritime safety.

5.1.2 Empirical study and results

The maritime occurrence probability model described above was applied using the total datasets and logistic regression procedure available within the SAS software. Two separate models were developed. In the first model, which classification society has higher occurrence probability of an accident and which flag has higher occurrence probability of an accident were tested. In the second model, three dummy variables were used to examine the effects of IACS, open registry and developed countries on the accident probability.

Table5-2 presents the logit regression of vessel occurrence probability of an accident for the model applications. The results indicate that the model fits the data well. For example, for Model I the likelihood ratio statistic is 14706, well above the 135.8 critical value for significance at the 0.01 level for 204 degrees of freedom. Most variables are highly significant, with p-values less than or equal to 0.01.

Table 5-2: Model fit summary

	Model I	Model II
Observation	127073	127073
Number of accidents	6930	6930
Number of non-accidents	120143	120143
Likelihood ratio	14706	9766.4
AIC	39455	44108
Schwarz criterion	41249	44508

Table 5-3 presents the partial effects of the coefficients and the significance level of interest variables. The sign of an estimated logit coefficient suggests either an increase or decrease in occurrence probability of an accident. The coefficient itself does not measure the correct marginal effect for non-zero observation of the dependent variable. The marginal effect can be derived utilizing the estimated coefficients and the following equation.

$$\frac{\partial P_k}{\partial x_k} = \frac{\partial(e^{\beta_0+\Sigma\beta_k x_k}/(1+e^{\beta_0+\Sigma\beta_k x_k}))}{\partial x_k} = \beta_k P(1-P) \qquad (5\text{-}3)$$

About the dummy variables, let $x_k$denote the dummy explanatory variable and x^+ denote the other covariates at their means. The effect due to a change of x_k on the predicted probabilities of y is$P(y = 1|x_k = 1, x^+) - P((y = 1|x_k = 0, x^+)$. The marginal effects results are listed in the last column.

The results of Model I suggests that an increase in vessel age is associated with an decrease in the vessel occurrence probability of an accident, which is contrary to our expectations, so Hypothesis 1 is rejected. An increase by 1 year in vessel age leads to a decrease by 0.001 in its occurrence probability of an accident. This is maybe a reflection of the fact that vessel owners pay more attention and put forth more effort on improvements of the safety level of older vessels then on those of younger ones. Secondly, older vessels may have been well tested to be regarded as quality tonnage (Cariou et al., 2008).

The second variable, which is measured by the gross tonnage, reveals that the occurrence probability of an accident increases as the vessel size increases.

$$\beta_2 = \frac{\Delta R}{\Delta ln x_2} = \frac{\Delta R}{\Delta x_2 / x_2} \qquad (5\text{-}4)$$

$$\Delta R = \beta_2 \times \Delta x_2 / x_2 \qquad (5\text{-}5)$$

The marginal effect of $x_2$suggests that the occurrence probability of an accident increases by 0.008% with a gross tonnage increase of 1%.

Table 5-3: Summary of main variables and their significance: Vessel Characteristics

Variable	Variable label	Variable type	Coefficient	P-value	Marginal probability
x1	Age	Continuous	-0.03	0.000	-0.001
x2	ln (gt)	Continuous	0.20	0.000	0.008
x3	General Cargo	Dummy	1.14	0.000	0.045
x4	Bulker	Dummy	0.33	0.000	0.013
x5	Container	Dummy	0.30	0.000	0.012
x6	Tanker	Dummy	0.17	0.006	0.007
x7	Passenger	Dummy	0.70	0.000	0.028

The coefficients for the vessel type dummy variables reveal that the occurrence probability of an accident vary among different vessel type groups (Table 5-3). The general cargo vessels group has the largest marginal effect on the occurrence probability of an accident, followed by the passenger vessels group. This means that the general cargo group of vessels is the type most at risk, and the second group most at risk is passenger vessels. The tankers group has the smallest marginal effect, so the occurrence probability of an accident of this group is lower. This study accepts Hypothesis 3d. The marginal effects are plotted along with the occurrence probability of an accident in Figures 2-7, using results from the logit model fit. These figures can help visualize the effect and give a better interpretation of the results. The marginal effects of age on the occurrence probability of an accident are obtained as a function of the age, at the mean of other variables, which are calculated using equation 5-3 and 5-5. As shown in Figure 5-1, the occurrence probabilities of accident are lower for newer vessels and general cargo vessels.

Figure 5-1: Effect of vessel age and vessel type on the probability

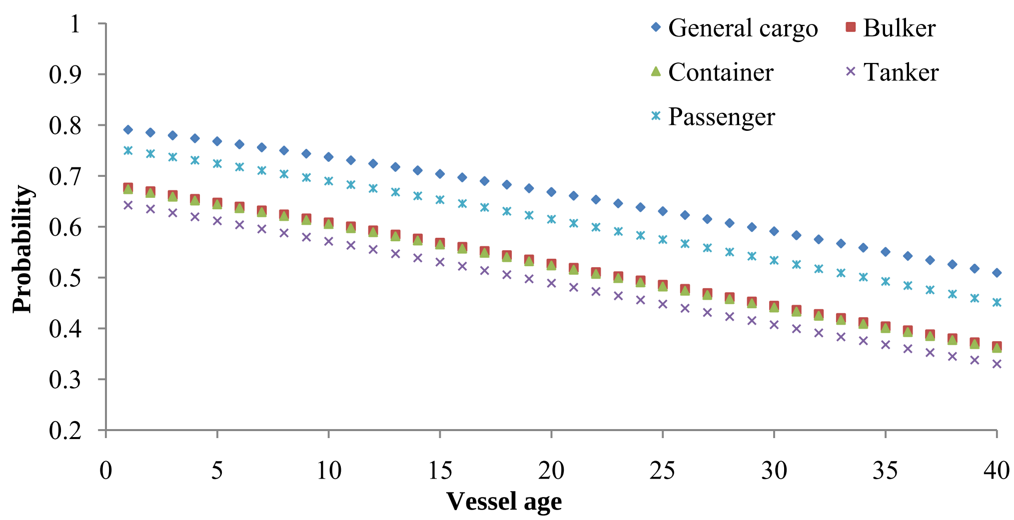
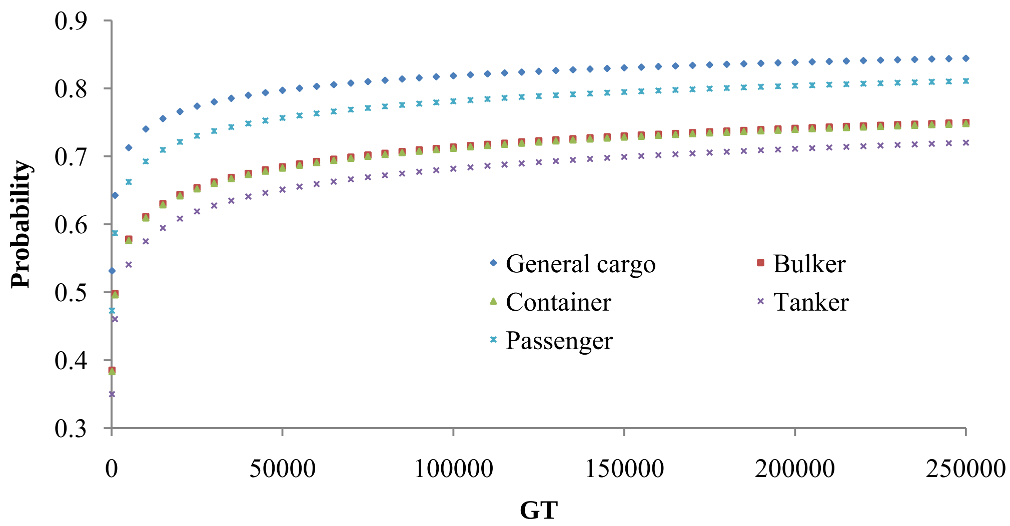


Figure 5-2: Effect of tonnage and vessel type on the probability



The occurrence probability of an accident is different among different classification societies, so Hypothesis 4a is accepted. Vessels registered with the American Bureau of Shipping and Nippon Kaiji have lower occurrence probability compared with other classification societies. The Registro Cubano has the least marginal effect on the occurrence probability of an accident, followed by the

Vietnamese Register. The results of the coefficients for classification societies are reported in Table 5-4. The results of Model II suggest that, compared with non-IACS members, vessels classified by IACS members are safer, so Hypothesis 4b is accepted. The negative value implies that a classification society with a good reputation ensures that the security of its vessels is sufficient for maritime adventure. That is because they enforce strict regulations so as to improve the security level of their vessels.

Figure5-3: Effect of vessel age and IACS on the probability

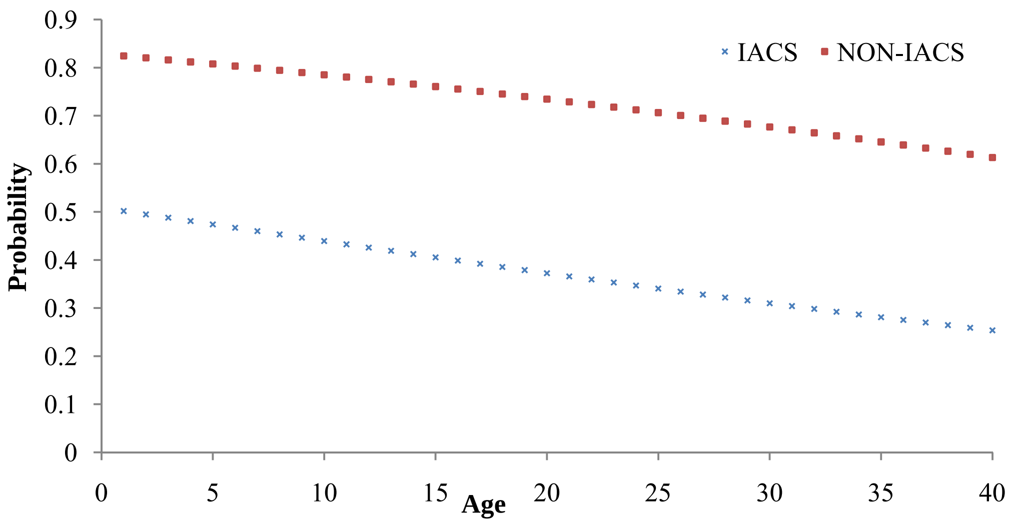
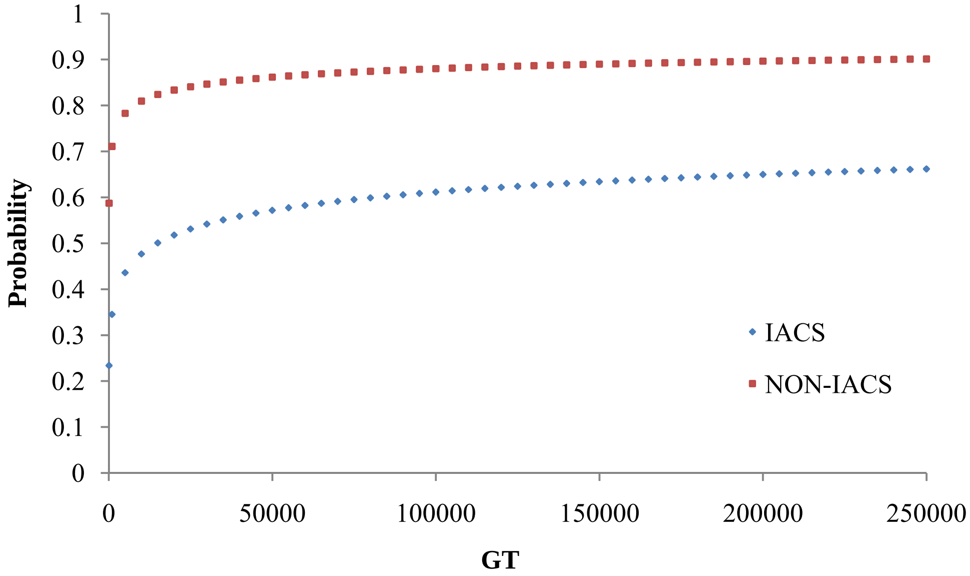


Figure 5-4: Effect of Tonnage and IACS on the probability



The coefficients (see Appendix Table A-2) for the vessel flag dummy variables (X40-X153) indicate that the occurrence probability of an accident is lower than the category "others" when the vessels are registered in Japan, China, Netherlands, India, Mexico, Brazil, Australia, Taiwan China, Sweden, Morocco, Belgium, South Africa and Ireland. The occurrence probability of an accident is higher when the vessel is registered in Panama, United States, Russia, Norway, Malta, Greece, Italy, Bahamas, Spain, Turkey, Honduras and Canada. This study accepts Hypothesis 6a.

Table 5-4 Summary of main variables and their significance: Classification Societies

Variable	Variable Label	Coefficient	P-value	Marginal Probability
x9	American Bureau of Shipping	-2.21	0.000	-0.088
x10	Bureau Veritas	-1.58	0.000	-0.063
x11	China Classification Society	-0.88	0.000	-0.035
x12	Det Norske Veritas	-1.85	0.000	-0.074
x13	Germanischer Lloyd	-1.64	0.000	-0.065
x14	South Korean Register	-1.42	0.000	-0.057
x15	Lloyds Register	-1.61	0.000	-0.064
x16	Nippon Kaiji	-2.00	0.000	-0.080
x17	Registro Italiano	-1.02	0.000	-0.041
x18	Russian Register	-1.22	0.000	-0.049
x19	Biro Klass Indonesia	-1.36	0.000	-0.054
x20	Bulgarski Koraben Registar	-1.06	0.035	-0.042
x21	China Corp Register	-0.01	0.958	-0.001
x22	Croation Register	-1.66	0.003	-0.066
x23	Hellenic Register	0.27	0.222	0.011
x24	Indian Register	-1.95	0.000	-0.078
x25	Yugoslavia Register	-0.31	0.958	-0.012
x26	Korea Classification Society	-0.63	0.027	-0.025
x27	Polish Register	-0.24	0.320	-0.010
x28	Turk Loydu	-0.23	0.208	-0.009
x29	Vietnamese Register	-2.48	0.000	-0.099
x30	Registro Cubano	-3.81	0.000	-0.152
x31	Rinave Portugesa	-0.86	0.116	-0.034
x32	Russian River Register	3.33	0.340	0.133
x33	East German Register	-0.27	0.967	-0.011
x34	Bulgarian Register of Shipping	6.00	0.206	0.239
x35	Isthmus Maritime Classification Society	1.88	0.590	0.075
x36	Isthmus Bureau of Shipping	3.72	0.255	0.148
x37	Maritime Lloyds-Georgia	4.69	0.141	0.187
x38	Romanian Register	4.04	0.006	0.161
X39	Other	8.09	0.250	0.322

As expected, the sign for the open registry (x185) coefficient is positive (Table 5-5), where Hypothesis 6b is accepted. This means that vessels registered in a flag-of-convenience country have higher occurrence probability of an accident, which probably because they have greater motivation to slacken off their security management.

Figure 5-5: Effect of vessel age and open registry on the probability

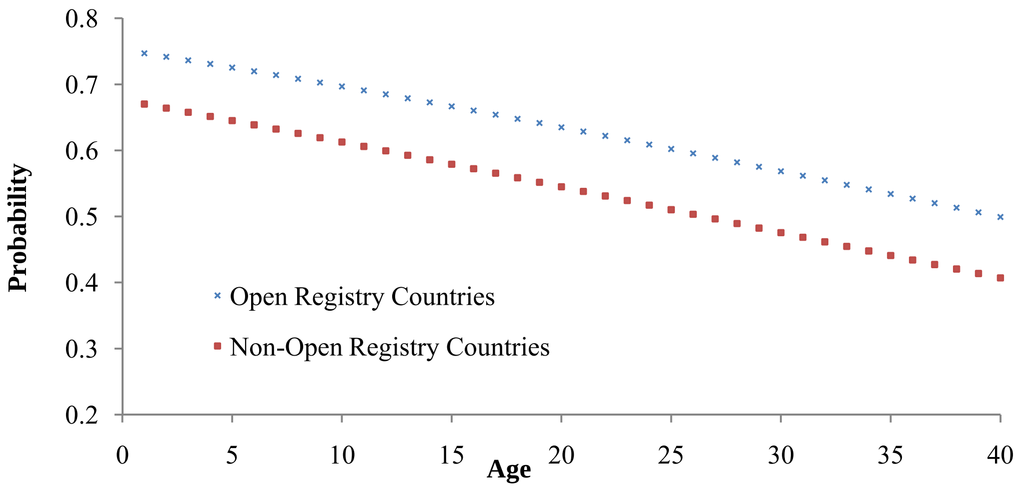


Figure 5-6: Effect of tonnage and open registry on the probability

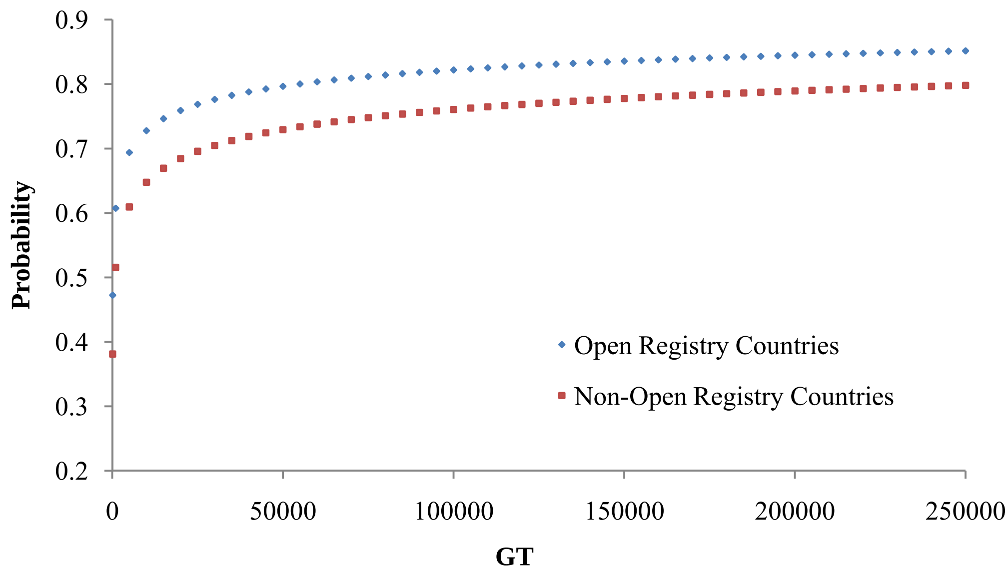


Table 5-5: Partial results of Model II

Variable	Variable label	Coefficient	P-value	Marginal probability
x8	IACS member	-1.5389	0.0001	-0.0690
X185	Open Registry Countries	0.3737	0.0001	0.0167
X186	Developed Countries	-0.0250	0.0001	-0.0011

Most of the coefficients (see table 5-6) of the zone variables are significant, except for zone 2, zone 14, zone 19 and zone 23, where Hypothesis 5 is accepted. The most dangerous zones include zone 3, 6, 8, 9, 10, 16, 17, and 18. Zone 6 is the Suez Canal. At present about 25,000 vessels pass through the canal every year. So this zone has an important effect on the maritime occurrence probability of an accident. The coefficients of two special zones (X166, X167) reveal that if the vessel voyage is via the Southern China Sea (zone 12) or the Eastern Asian (zone 13) these have no significant effect on decreasing the occurrence probability of an accident. The large number of accidents may be because the number of vessel voyages via these two zones is larger.

The incident season (X187-x189) does not seem to have a significant effect on the vessel occurrence probability of an accident, and the coefficients of the year (X190-X205) aren't significant either. So that means that some conditions, such as technological changes, regulations and congestion, vary through time but have no significant effect on the occurrence probability of an accident of vessels. So Hypothesis 7a and Hypothesis 7b are rejected. The season and year cannot indicate a vessel's occurrence probability of an accident.

In summary, the vessel occurrence probability of an accident is primarily influenced by a vessel's age, its type, its classification society and its flag. Within the external factors, only the incident zone has the significant effect on the vessel's occurrence probability of an accident.

When a vessel's characteristic data is available, the probability of the vessel being involved in an accident can be got. For each vessel an individual probability of accident can obtained.

Table 5-6: Summary of main variables and their significance: Zone

Variable	Coefficient	P-value	Marginal Probability
zone1	0.81	0.0000	0.032
zone2	0.02	0.8620	0.001
zone3	11.88	0.2030	0.473
zone4	-1.11	0.0000	-0.044
zone5	-1.57	0.0000	-0.063
zone6	2.72	0.0000	0.108
zone7	-1.3	0.0000	-0.052
zone8	1.53	0.0000	0.061
zone9	1.14	0.0000	0.045
zone10	2.63	0.0000	0.105
zone11	0.41	0.0090	0.016
zone12	-1.35	0.0000	-0.054
zone13	-0.49	0.0000	-0.02
zone14	11.27	0.2630	0.449
zone15	-0.69	0.0010	-0.027
zone16	2.81	0.0000	0.112
zone17	10.52	0.3050	0.419
zone18	2.07	0.0000	0.083
zone19	-0.08	0.4240	-0.003
zone20	-2.15	0.0000	-0.085
zone21	-2.63	0.0000	-0.105
zone22	-2.06	0.0000	-0.082
zone23	0.07	0.5740	0.003
zone24	0.7	0.0000	0.028
zone25	2.55	0.0000	0.102
zone26	11.54	0.1810	0.46
zone27	-0.55	0.0080	-0.022
zone28	2.61	0.0000	0.104
zone29	-1.16	0.0000	-0.046
zone30	-3.3	0.0000	-0.132

5.2 Consequence estimation

In terms of cost, the loss of different ships under different situations may be various. The market value of second hand vessels is used to show the levels of losses for ships with different ages and sizes (Table 5-7).

Table 5-7: Estimated losses due to accidents under different conditions (US$M)

Vessel age	New		Average		Old	
Vessel size	Smaller	Larger	Smaller	Larger	Smaller	Larger
bulk	-31	-67	-28	-53	-11	-20
tankers	-14	-80	-9	-40	-7.6	-15
Container	-30	-104	-22	-75	-10	-38
Gen cargo	-10	-20	-3	-5.6	-2	-4.4
Source:	Clarkson: Shipping Intelligence Network, 2009					

We cannot observe risk directly, but we can measure the probability of the occurrence of an accident through historical data on safety indicators, such as vessel age, type, registration and classification. We investigate the effects of various risk factors and the use of multivariate logistic regression modeling to assess how the various factors simultaneously affect the probability of accident.

The results will continue to be improved, with dynamic information regarding updated vessel movements and management changes, as well as accurate inspection and survey reports.

Chapter 6：Risk analysis using Bayesian Network

This section presents an innovative approach toward integrating logistic regression and Bayesian Networks (BN) together into risk assessment. The approach has been developed and applied to a case study in the maritime industry, but with potential of being adapted in other industries.

Various applications of Bayesian Networks (BN) as a modeling tool in maritime risk analysis have been widely seen in the relevant literature. However, a common criticism against the Bayesian approach is that it requires too much information in the form of prior probabilities, which information is often difficult, if not impossible, to obtain in risk assessment. A traditional and common way to estimate the prior probability of accidents is to use expert estimation (inputs) as a measure of uncertainty in risk analysis. To address the inherited problems associated with subjective probability (expert estimation), this study develops a binary logistic regression method to provide input for a BN, making use of different maritime accident data resources. Relevant risk assessment results have been achieved to measure the occurrence probability of an accident of different types of vessels under different situations.

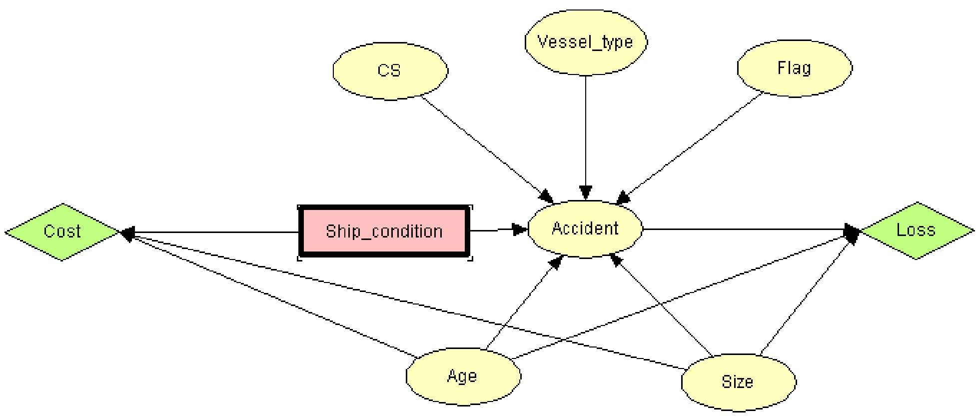
6.1 Maritime risk analysis using Bayesian Network

6.1.1 Establish nodes with dependencies

The first step is to set up the nodes with relevant dependencies. Based on previous research and analysis of casualty data, nodes that have been established to indicate influencing factors on maritime accidents include vessel age and size, along with the efforts made by flag states, classification societies (CS).

Vessel age, size, flag, classification society and vessel type have been identified as the major contributory factors to ship accidents. Although there are some other influencing factors, a careful analysis of historical accident data has indicated that their effects on the probability of accident are relatively trivial. The proposed framework, including all the factors that may contribute to an accident, is illustrated in Figure 1.

Figure 6-1: The shipping accident model using BN



The BN consists of three types of nodes. The first type is the chance node. CS) vessel type, vessel flag (Flag), age and size do not have any parents. The accident is a child node. The links between the nodes represent causal relationships between the nodes. An arrow means that the parent's node has an impact on the state of the child node. As the second type, the rectangle represents a decision node (ship condition). The arrow between the decision node and the accident node means that the decision has an impact on the occurrence probability of an accident.

The utility node (Cost), the third type of node, is associated with the state of the decision node. The utility node has a utility function enabling the computation of the expected utility of a decision. The cost node represents the cost associated with the ship's conditions, which at the same time depends on the states of age and size. Another utility node, loss, gathers information about the loss once the accident happens. In the same way, the magnitude of the loss depends on the state of vessel age and size.

6.1.2 Create CPT and prior probabilities for each node

The next step is to establish a CPT for each node. The following equation shows the model used to estimate the occurrence probability of an accident.

$$X\beta_i = \beta_0 + \beta_1 VA + \beta_2 VS + \sum_{i=1}^{5} \beta_{i+2} VT_i + \beta_8 CS + +\beta_9 FS + \sum_{j=1}^{30} \beta_{j+9} Z_j \quad (6\text{-}1)$$

where vessel age (VA) and vessel size (VS) are continuous variables. Vessel types (VT) include dry cargo ship, bulker, container ship, tanker and passenger ship, as dummy variables. $VT_1 = 1,$ if it is a dry cargo ship; otherwise $VT_1 = 0$. The classification society (CS) and flag state (FS) are also dummy variables. If the vessel is classified by a member of the International Association of Classification Societies (IACS), then $CS = 1$, otherwise $CS = 0$. If the vessel's flag is open registry, then $FS = 1$; otherwise $FS = 0$. z_j are 30 control dummy variable. In accordance with the world casualty statistics, the whole of the world's ocean region has been divided into 31 zones. Due to their unique geographical environment, different regions will have different effects on the probability of accident. z_j were used to control them.

The model can be processed using the data collected, and the logistic regression procedure is available within the SAS software. (SAS, 1990)

Table 6-1 presents the logit regression of vessel occurrence probability of an accident for the model applications and partial effects of the coefficients, and the significance level of the variables of interest. The results indicate that the model fits the data well. The likelihood ratio statistic is 9766.4, which is well above the 20.09 critical value for significance at the 0.01 level for 8 degrees of freedom. All the variables are highly significant, with p-values less than 0.01. The sign of an estimated logistic coefficient suggests either an increase or decrease in the probability of an accident occurring.

Table 6-1: Model fit summary

Variable	Variable label	Coefficient	P-value	Variable	Variable label	Coefficient	P-value
β_0	Constant	-3.68	0.000	Z11	Zone11	-0.59	0.000
VA	Vessel age	-0.03	0.000	Z12	Zone12	-1.38	0.000
VS	Vessel size ln (gt)	0.24	0.000	Z13	Zone13	-0.58	0.000
VT1	Dry cargo	1.11	0.000	Z14	Zone14	19.12	0.971
VT2	Bulker	0.33	0.000	Z15	Zone15	-0.80	0.000
VT3	Container	0.33	0.000	Z16	Zone16	1.26	0.000
VT4	Tanker	0.07	0.006	Z17	Zone17	14.12	0.847
VT5	Passenger	0.72	0.000	Z18	Zone18	1.00	0.000
CS	Classification Societies	-1.54	0.000	Z19	Zone19	0.05	0.535
FS	Flag state	0.37	0.000	Z20	Zone20	-1.19	0.000
Z1	Zone1	0.73	0.000	Z21	Zone21	-1.73	0.000
Z2	Zone2	0.27	0.000	Z22	Zone22	-1.80	0.000
Z3	Zone3	21.93	0.000	Z23	Zone23	0.19	0.051
Z4	Zone4	-0.63	0.000	Z24	Zone24	0.68	0.000
Z5	Zone5	-1.02	0.000	Z25	Zone25	1.24	0.000
Z6	Zone6	2.67	0.000	Z26	Zone26	23.01	0.000
Z7	Zone7	-1.14	0.000	Z27	Zone27	0.22	0.083
Z8	Zone8	0.83	0.000	Z28	Zone28	2.65	0.000
Z9	Zone9	0.82	0.000	Z29	Zone29	-0.60	0.000
Z10	Zone10	1.16	0.000	Z30	Zone30	-1.40	0.000

Using the above result, when a vessel's characteristic data is available, the probability of the vessel being involved in an accident can be predicted using Equation (6-2).

$$\hat{p}_i = \frac{e^{\sum \beta_i X}}{1+e^{\sum \beta_i X}} \tag{6-2}$$

In the binary regression, X_i contains independent variables such as age, size, flag and CS. Some subjective causes, such as the shipowners' efforts and crew training, as well as certain objective causes, such as the ship's safety equipment and structure are not representing by those variables. These components are all associated with the ship's safety condition. In this research the π_i were used to categorize the ships as being standard or substandard. π_i were defined as:

$$\pi_i = y_i - \hat{p}_i = y_i - \frac{e^{\sum \beta_i X}}{1+e^{\sum \beta_i X}} \tag{6-3}$$

where y_i is the observed result of one accident $(y_i = 1)$ or non-accident $(y_i = 0)$, and $\hat{p}_i$ is the predicted probability of the vessel being involved in an accident.

A positive π_i means that the accident has happened, but that the estimated probability of casualty is less than 1. This means that this accident could have been avoided and that this shipowner could have made substandard efforts, or that the safety equipment was not good enough. This type of ship was defined as a substandard ship.

A negative π_i means that the estimated probability of casualty is larger than 0, but that the ship has not been involved in an accident, which indicates that this shipowner could have made standard efforts, or that the ship's safety condition is good, which decreases the probability of accident occurrence. This type of ship was defined as a standard ship.

Certainly, π_i could include other information besides the ship's safety conditions, though it may be trivial. With further development of the dynamic shipping database, even more variables may be used to measure a ship's safety conditions more accurately.

In Equation (4), the VA and VS as continuous variables need to be transformed into dummy variables when being modeled in BNs. According to different ages, VA has been separated into 3 groups. For example, the average age of a containership is 6.3. 3 groups based on their ages are defined as new (≤ 5years), average (6-10 years) and old (> 10 years). Similarly, VS has been separated into 2 groups based on the average ship size. The proportion of each group defined is used as the conditional probability of each node in the BN model. For example, 92.38% of containerships are classified by IACS members, whereas only 32.36% of passenger ships are classified by IACS members. Table 2 lists the conditional probabilities of each node using the model.

Table 6-2: The conditional probability of each node

	%	Container	Dry Cargo	Bulk	Tanker	Passenger
CS	Non-IACS (CS1)	7.62	59.53	21.94	31.82	67.64
	IACS (CS2)	92.38	40.47	78.06	68.18	32.36
FS	Closed Registered (FS1)	38.87	63.66	34.09	53.36	80.57
	Open Registered (FS2)	61.13	36.34	65.91	46.64	19.43
VA	New (VA1)	51.35	23.91	56.44	48.74	24.18
	Medium (VA2)	14.51	18.34	18.08	18.93	23.69
	Old (VA3)	34.14	57.75	25.48	32.33	52.13
VS	Smaller than Average (VS1)	47.33	48.64	37.91	52.88	62.85
	Larger than Average (VS2)	52.67	51.36	62.09	47.12	37.15

When putting the coefficient β_i into Equation (6-2), it is possible to obtain the conditional probabilities of an accident. The CPT is too large to show in one network due to the fact that there are 7 nodes in this model. Table 3 lists the containership's conditional probabilities of an accident under different conditions. Other conditional probabilities are shown in the appendix.

Table 6-3: The conditional probability of an accident under different conditions

Ship safety condition	Standard											
Vessel size	Smaller											
Vessel age	New				Average				Old			
Flag state	Closed		Open		Closed		Open		Closed		Open	
Classification society	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS
Accident	0.08	0.05	0.33	0.06	0.05	0.04	0.19	0.05	0.05	0.03	0.07	0.04
Non-accident	0.92	0.95	0.67	0.94	0.95	0.96	0.81	0.95	0.95	0.97	0.93	0.96

Ship safety condition	Standard											
Vessel size	Larger											
Vessel age	New				Average				Old			
Flag state	Closed		Open		Closed		Open		Closed		Open	
Classification society	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS
Accident	0.2	0.07	0.18	0.08	0.31	0.05	0.43	0.07	0.35	0.04	0.09	0.04
Non-accident	0.8	0.93	0.82	0.92	0.69	0.95	0.57	0.93	0.65	0.96	0.91	0.96

Table 6-3: The conditional probability of an accident under different conditions (Continue)

Ship safety condition	Substandard											
Vessel size	Smaller											
Vessel age	New				Average				Old			
Flag state	Closed		Open		Closed		Open		Closed		Open	
Classification society	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS
Accident	0.12	0.21	0.3	0.19	0.15	0.19	0.2	0.19	0.13	0.09	0.19	0.18
Non-accident	0.88	0.79	0.7	0.81	0.85	0.81	0.8	0.81	0.87	0.91	0.81	0.82
Ship safety condition	Substandard											
Vessel size	Larger											
Vessel age	New				Average				Old			
Flag state	Closed		Open		Closed		Open		Closed		Open	
Classification society	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS
Accident	0.34	0.22	0.52	0.22	0.2	0.2	0.21	0.32	0.37	0.12	0.4	0.17
Non-accident	0.66	0.78	0.48	0.78	0.8	0.8	0.79	0.68	0.63	0.88	0.6	0.83

6.1.3 Maintenance cost and accident loss

The repair and maintenance cost is a vital element in the operations of any shipowner. Numerous factors affect both the amount and the time of repair and maintenance. Vessel age, steel price and even regional price differentials will all affect the maintenance cost. A simple example is presented here to demonstrate the effect on cost. Normally, the repair cost increases with vessel age. Approximate repair and maintenance costs were estimated by Drewry Shipping Consultants Ltd (Drewry annual report 2007/08). Although there may be significant variations around these estimates, the information presents some 'rule of thumb' guidelines for this analysis. Such cost estimates are summarized in Table 6-4.

Table 6-4: Estimated approximate repair and maintenance costs based on the age variable

Age (Years)	Scheduled Repair	Unscheduled Repair
0-4	0.80	0.40
5-9	1.00	1.00
10-14	1.25	1.75
15-20	1.60	2.00
>20	2.00	1.35

Note: The base cost level relates to ships of 5-9 years of age
Source: Drewry, 2007

If the ship belongs to a standard ship, both the scheduled and unscheduled repair and maintenance work is done by the shipowner. If only scheduled repairs are done by the shipowner, then the ship is a substandard ship.

The maintenance cost data was gathered from Drewry's publication *Ship Operating Cost Annual Review and Forecast 2007/08*. The database includes the repair and maintenance costs for different types of vessels of different sizes for the period 2001-2010. In Table 6-5, the repair and maintenance costs are estimated for different conditions.

Table 6-5: Estimated approximate repair and maintenance costs under different conditions ($)

Vessel size	Smaller					
Vessel age	New		Average		Old	
Ship safety condition	Std	Substd	Std	Substd	Std	Substd
Bulk	-200175	-120105	-440385	-190166	-447057	-266900
Tanker	-383775	-230265	-844305	-364586	-857097	-511700
Container	-168510	-101106	-370722	-160084	-376339	-224680
Dry cargo	-157650	-94590	-346830	-149767	-352085	-210200
Vessel size	Larger					
Vessel age	New		Average		Old	
Ship safety condition	Std	Substd	Std	Substd	Std	Substd
Bulk	-319650	-191790	-703230	-303667	-713885	-426200
Tanker	-580650	-348390	-1277430	-551617	-1296785	-774200
Container	-208200	-124920	-458040	-197790	-464980	-277600
Dry cargo	-184650	-110790	-406230	-175417	-412385	-246200

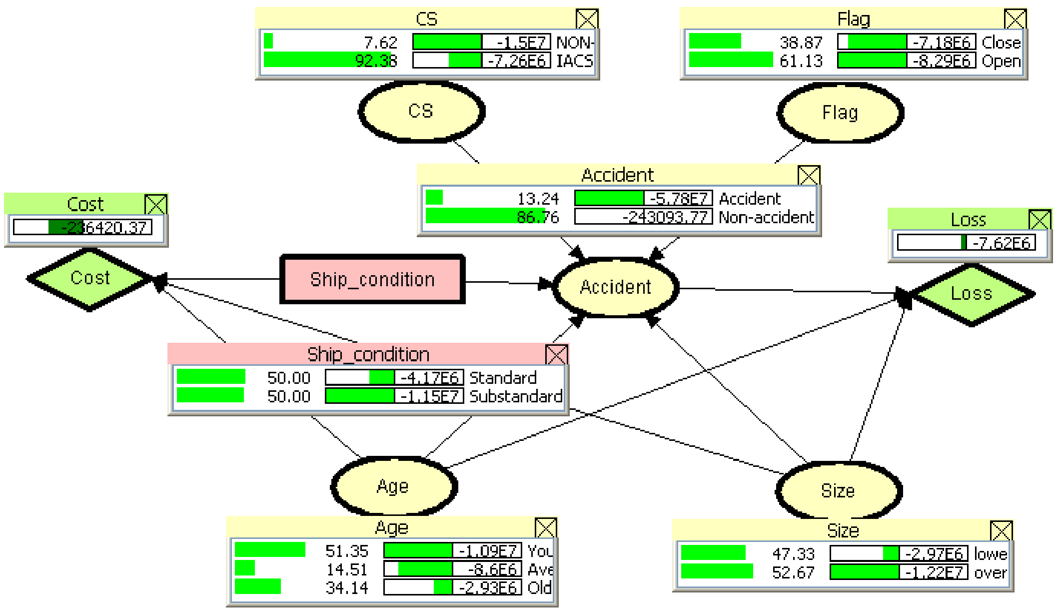
In terms of cost, the loss of different ships under different situations can be diverse. An example in Table 6-6 is used to show the levels of losses for ships of different ages and sizes.

Table 6-6: Estimated losses due to accidents under different conditions ($M)

Vessel age	New		Average		Old	
Vessel size	Smaller	Larger	Smaller	Larger	Smaller	Larger
Bulk	-31	-67	-28	-53	-11	-20
Tanker	-14	-80	-9	-40	-7.6	-15
Container	-30	-104	-22	-75	-10	-38
Dry cargo	-10	-20	-3	-5.6	-2	-4.4

Having established the CPT for each node and the utility table for each configuration of decision alternative and outcome state for the determining variable, normalization is required, which means that the probability values should be non-zero and have a combined value for each CPT of 1. Inputting both the probability data and the utility data into the Hugin software (Hugin, 2008), normalization has been carried out automatically by this software. A prior probability of accident can also be obtained. With regard to container ships, taking into account all of the prior probabilities, the probability of accident is estimated to be 23.69%. This is illustrated in Figure 6-2.

Figure 6-2: Prior probability of containerships' accidents



The capacity for drawing inference is the great advantage of the BN statistical tool. BN is useful for estimating, in probabilistic terms, changes in one or more variables in response to the introduction of new evidence. Sensitivity refers to how sensitive a model's performance is to minor changes in the input parameters. Sensitivity analysis is particularly useful in investigating the effects of inaccuracies or incompleteness in the parameters of a BN model on the model's output. The most natural way of performing sensitivity analysis is to change the parameters' values and then, using an evidence propagation method, to monitor the effects of these changes on the posterior probabilities. Thus one of the most important sensitivity analysis aspects is to analyze how they change when prior probabilities take different values.

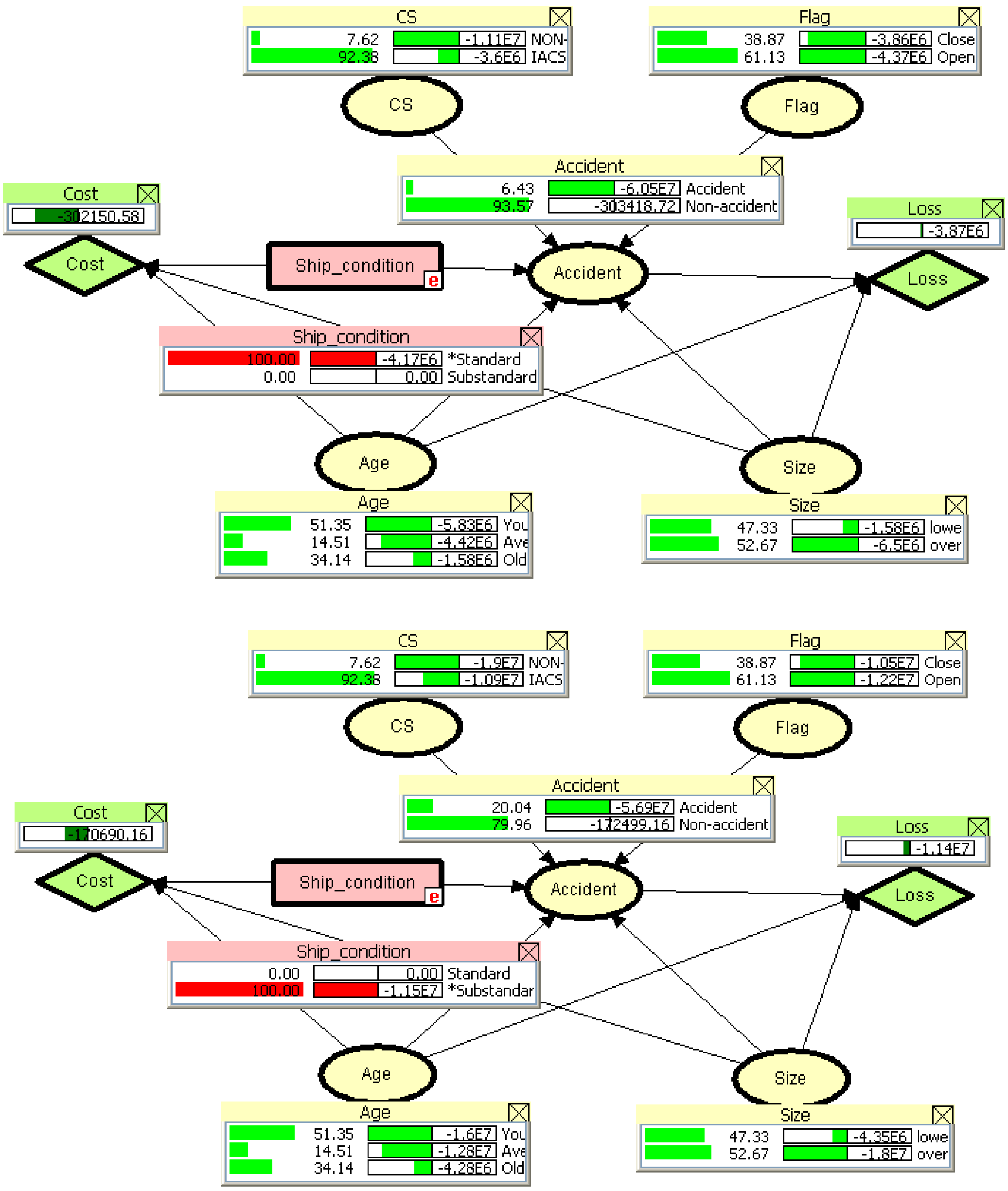
6.2 The effect of different factors

6.2.1 The effect of ship safety condition

Ship safety condition has an important effect on the probability of an accident occurrence. Having locked all the other nodes, meaning that those parameters will not change, a useful scenario that can be run in this model is to simulate both standard and substandard ships. Figure 6-3 illustrates the effect of containership condition.

In this scenario, if a ship is a standard ship (100% standard nodes), it can be observed in Figure 6-3 that the accident probability will decrease to 6.43%. If, on the other hand, the ship is substandard (100% substandard node), it can be observed that the accident probability will increase to 20.04%.

Figure 6-3: Effect of ships safety condition on the probability of an accident (containership)



The sensitivity analysis with respect to the given vessel types are shown in

Table 6-7. As can be seen in the last column of Table 6-7, changes to the posterior probabilities are evident in the accident occurrence probability when a ship's safety condition changes from standard to substandard. The average change for the given vessel types is 142.35%. The largest change among them is containership (211.66%), and bulk carriers (163.52%). Passenger ships are least effected by ship safety condition (90.42%).

Table 6-7: The effect of ship safety condition

Type	Prior probabilities	Posterior probabilities		Changes to posterior probabilities (%)
		Standard	Substandard	
Container	13.24	6.43	20.04	211.66
Dry Cargo	13.41	8.82	18.00	104.08
Bulk	12.91	7.10	18.71	163.52
Tanker	8.74	5.11	12.37	142.07
Passenger	9.25	6.37	12.13	90.42
		Average change (%)		142.35

Table 6-8 shows the expected loss for the different safety conditions. The expected loss if the standard containership has an accident is \$3.87M, and the cost of maintaining a standard containership is \$0.3M, so the expected overall cost to the shipowner is \$4.17M. However, with regard to a substandard containership, the expected loss for the accident is \$11.4M, and the total cost of a standard containership is \$0.17M. The expected overall cost to the shipowner is therefore \$11.57M, which is a significant increase compared to the previous figure of \$4.17M, which is the largest different (177.33%) followed by bulk carriers (121.4%).

Dry cargo ship has the least different (48.19%) between standard and substandard ships. We can therefore conclude that although the maintenance cost is higher to keep a standard ship, the expected overall cost is lower than that of operating a substandard ship.

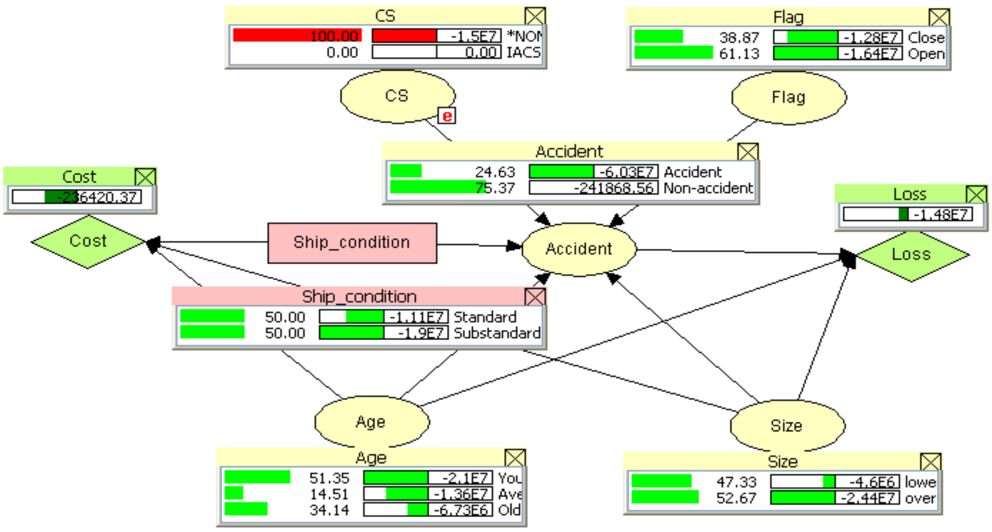
Table 6-8: The expect accident loss under different safety condition ($M)

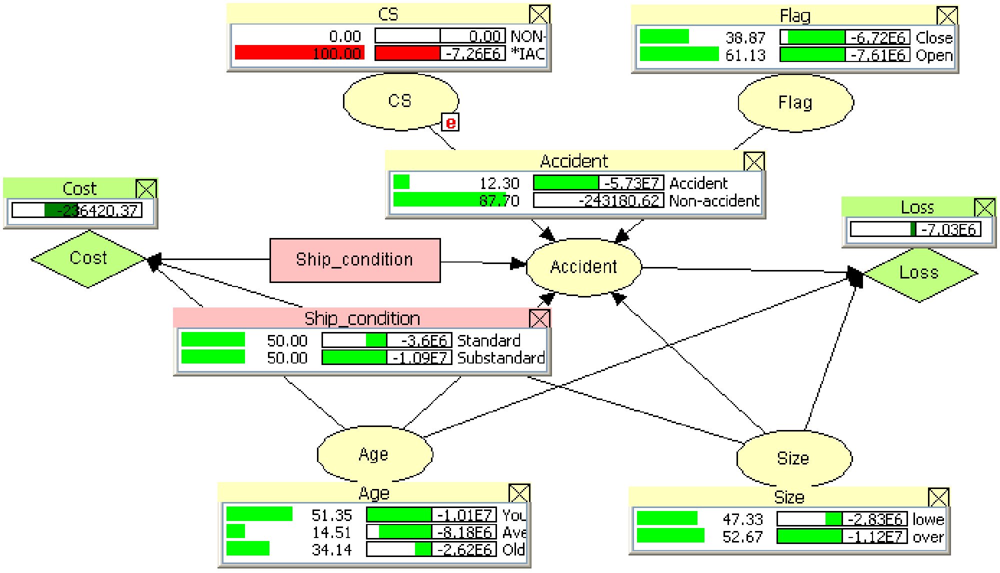
Type	Std			Substd			Differents (%)
	M&R cost	Loss	Total	M&R cost	Loss	Total	
Container	0.30	3.87	4.17	0.17	11.40	11.57	177.33
Dry Cargo	0.33	0.73	1.06	0.19	1.39	1.58	48.19
Bulk	0.42	3.52	3.94	0.23	8.49	8.72	121.40
Tanker	0.77	2.12	2.89	0.19	4.67	4.86	68.05

6.2.2 The effect of classification society

Figure 6-4 illustrates the effect of IACS members on the probability of occurrence of accidents (containerships).

Figure 6-4: Ship classification societies' effects on the probability of accidents (containerships)





As seen in Figure 6-4, if a ship is classified by a member of the IACS (100% IACS), the accident probability will decrease to 12.30%. If, on the other hand, a ship is classified by a non-IACS member (100% non-IACS), the accident probability will increase to 24.63%.

The sensitivity analysis results of the five vessel types are shown in Table 6-9. As seen in the last column of Table 6-9, changes between the posterior probabilities are evident when the ship's classification society changes from that of an IACS member to a Non-IACS member. The average change of the five vessel types is 103.95%. The largest change among them is with passenger ships (129.61%), and then bulk carriers (113.65%). The least affected by the classification societies is dry cargo ships (64.01%).

Table 6-9: The effect of classification society

Type	Prior probabilities	Posterior probabilities		Changes rate between posterior probabilities (%)
		IACS	Non-IACS	
Container	13.24	12.3	24.63	100.24
Dry Cargo	13.41	9.17	16.3	77.75
Bulk	12.91	10.33	22.07	113.65
Tanker	8.74	6.65	13.2	98.50
Passenger	9.25	4.93	11.32	129.61
		Average change (%)		103.95

Table 6-10 shows the expected loss for the different classification society. The expected loss of a container ship is classified by a member of the IAC has an accident is \$7.03M, and the cost of maintaining a containership is \$0.24M, so the expected overall cost to the shipowner is \$7.27M. However, with regard to a containership is classified by a member of the IAC, the expected loss for the accident is \$14.8M. The expected overall cost to the shipowner is therefore \$15.04M, which is a significant increase compared to the previous figure of \$7.27M, which is the second largest different (106.93%) follows bulk carriers (120.24%). Dry cargo ship has the least different (56.57%) between IACS and Non IACS ships. We can therefore conclude that the expected overall cost of a ship is classified by a member of the IACS is lower than that ship is classified by a member of the Non-IACS.

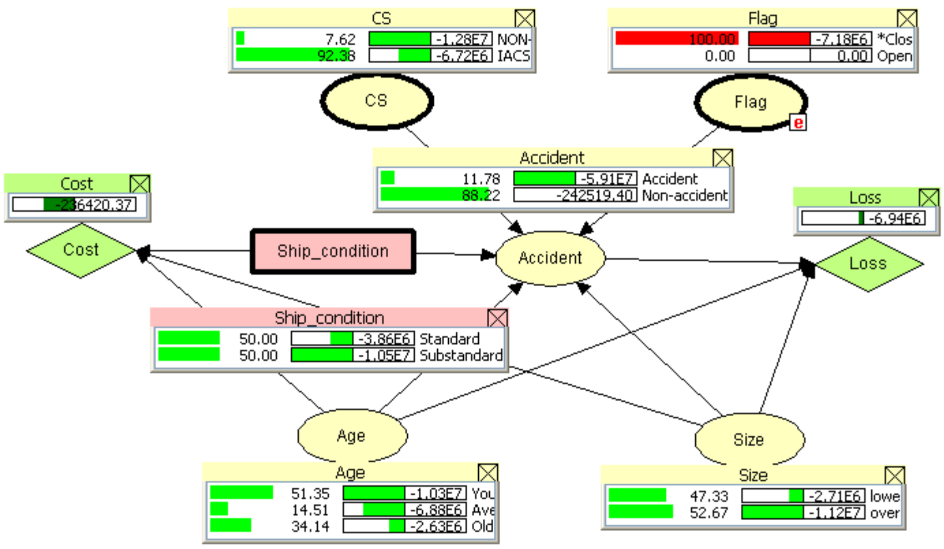
Table 6-10: The expect accident loss under different classification society ($M)

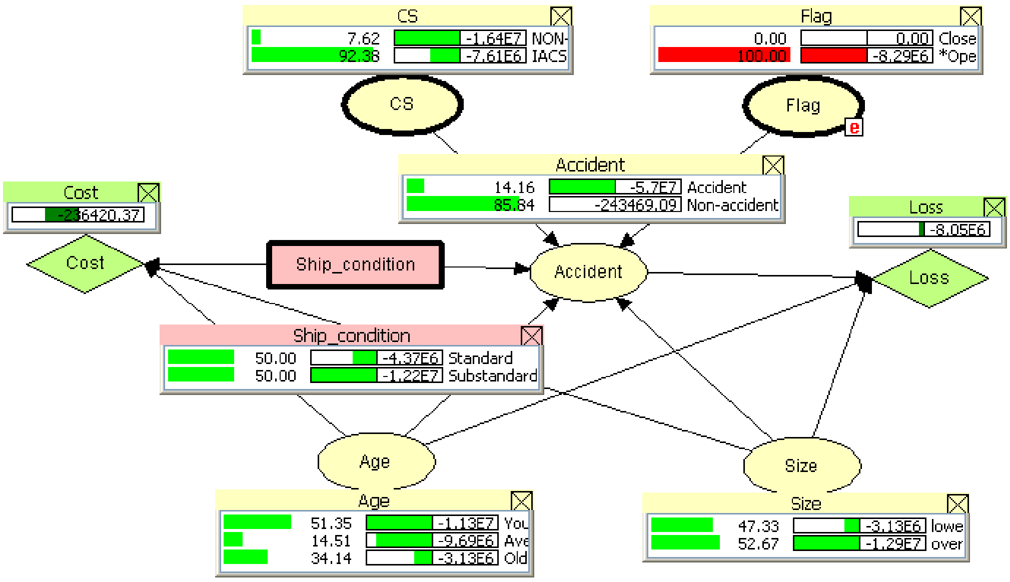
Type	IACS			Non IACS			Differents (%)
	M&R cost	Loss	Total	M&R cost	Loss	Total	
Container	0.24	7.03	7.27	0.24	14.80	15.04	106.93
Dry Cargo	0.26	0.73	0.99	0.26	1.29	1.55	56.57
Bulk	0.33	4.68	5.01	0.33	10.70	11.03	120.24
Tanker	0.48	2.51	2.99	0.48	5.30	5.78	93.16

6.2.3 The effect of flag state

A vessel registered in a FOC country probably has a greater intention of slackening off its safety management, which may result in a higher accident possibility.

Figure 6-5: The effect of vessel's flag state (containership)





As seen in Figure 6-5, if a ship is registered in a closed registry (100% FS1 variables), the accident probability will decrease to 11.78%. If, on the other hand, the ship is registered in an open registry (100% FS2 variables), the accident probability will increase to 14.16%.

The sensitivity analysis results of the five vessel types are shown in Table 6-11. As seen in the last column of Table 6-11, changes to the posterior probabilities are clearly evident when a ship's registration changes from an open registry to a closed one. The average change of the five vessel types is 19.79%. The largest change among them is dry cargo ships (29.64%), followed by bulk carriers (29.42%). The least affected by flag states is passenger ships (6.79%).

Table 6-11: The effect of flag state

Type	Prior probabilities	Posterior probabilities		Changes rate between posterior probabilities (%)
		Closed	Open	
Container	13.24	11.78	14.16	20.20
Dry Cargo	13.41	12.11	15.7	29.64
Bulk	12.91	10.81	13.99	29.42
Tanker	8.74	8.21	9.27	12.91
Passenger	9.25	9.13	9.75	6.79
		Average change (%)		19.79

Table 6-12 shows the expected loss for the different flag state. The expected loss of a container ship register in a closed flag state has an accident is \$6.94M, and the cost of maintaining a containership is \$0.24M, so the expected overall cost to the shipowner is \$7.18M. However, with regard to a containership is register in a closed flag state, the expected loss for the accident is \$8.05M. The expected overall cost to the shipowner is therefore \$8.29M, which is a significant increase compared to the previous figure of \$7.18M, which is the least different (15.47%).

Tanker ship has the largest different (24.89%), followed by dry cargo ship (24.25%) between closed and open register countries. We can therefore conclude that the expected overall cost of a ship register in a closed register countries is lower than that ship register in an open register countries.

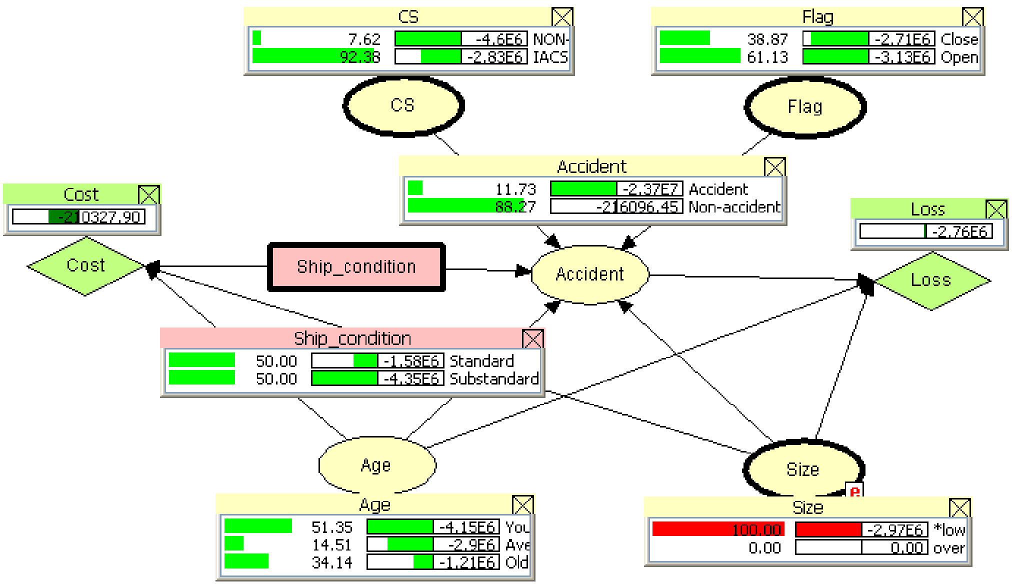
Table 6-12: The expect accident loss under different flag state ($M)

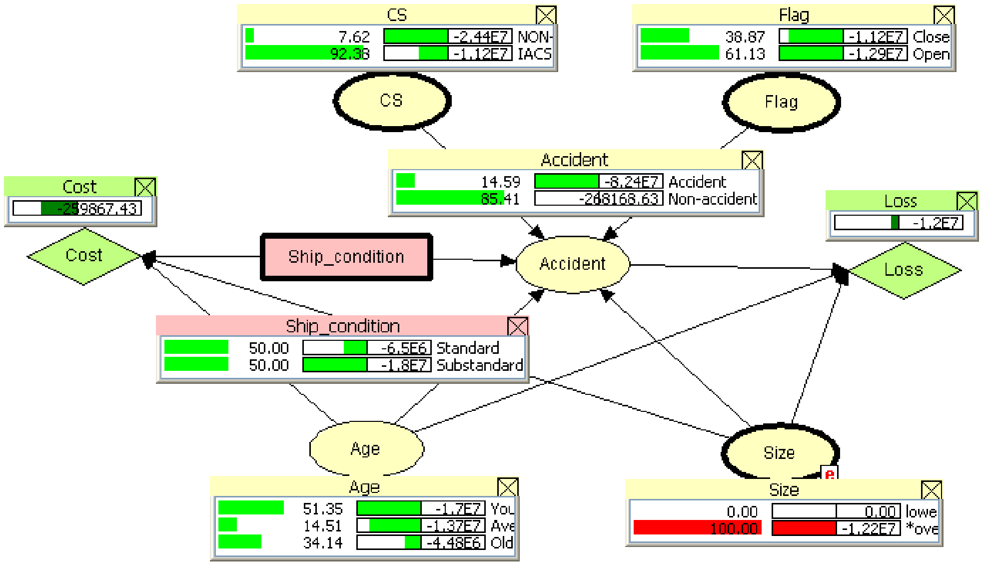
Type	Closed			Open			Differents (%)
	M&R cost	Loss	Total	M&R cost	Loss	Total	
Container	0.24	6.94	7.18	0.24	8.05	8.29	15.47
Dry Cargo	0.26	0.96	1.21	0.26	1.25	1.51	24.25
Bulk	0.33	5.22	5.55	0.33	6.42	6.75	21.63
Tanker	0.48	2.97	3.45	0.48	3.83	4.31	24.89

6.2.4 The effect of vessel size

When a vessel's size increases, its maneuverability at sea may be reduced, leading to a greater chance of its being involved in an accident.

Figure 6-6: The effect of vessel size (containership)





As seen in Figure 6-6, if a ship has a large size, the accident probability increases to 14.59%. If, on the other hand, the ship has a small size, the accident probability decreases to 11.73%.

The sensitivity analysis results of the five vessel types are shown in Table 6-13. As seen in the last column of Table 6-13, there are changes to the posterior probabilities when evidence changes from a large ship to a small ship. The average change of the five vessel types is 69.38%. The largest change among them is tankers (157.17%), followed by passenger ships (83.57%). The least affected by vessel size is ontainerships (24.38%).

Table 6-13: The effect of vessel size

Type	Prior probabilities	Posterior probabilities		Changes rate between posterior probabilities (%)
		VS1	VS2	
Container	13.24	11.73	14.59	24.38
Dry Cargo	13.41	10.47	16.2	54.73
Bulk	12.91	11.05	14.04	27.06
Tanker	8.74	5.02	12.91	157.17
Passenger	9.25	7.06	12.96	83.57
		Average change (%)		69.38

Table 6-14 shows the expected loss for the different vessel size. The expected loss of a lower size tanker ship is \$0.57M, and the cost of maintaining a containership is \$0.49M, so the expected overall cost to the shipowner is \$1.05M. However, with regard to an oversize tanker, the expected loss for the accident is \$6.57M, and the cost of maintaining is \$0.48M, The expected overall cost to the shipowner is therefore \$7.05M, which is a significant increase compared to the previous figure of \$1.05M, which is the largest different (570.99%).

Bulk carrier has the largest different (161.86%) between lower and over size ship. We can therefore conclude that the expected overall cost of a lower size ship is lower than that over size ship.

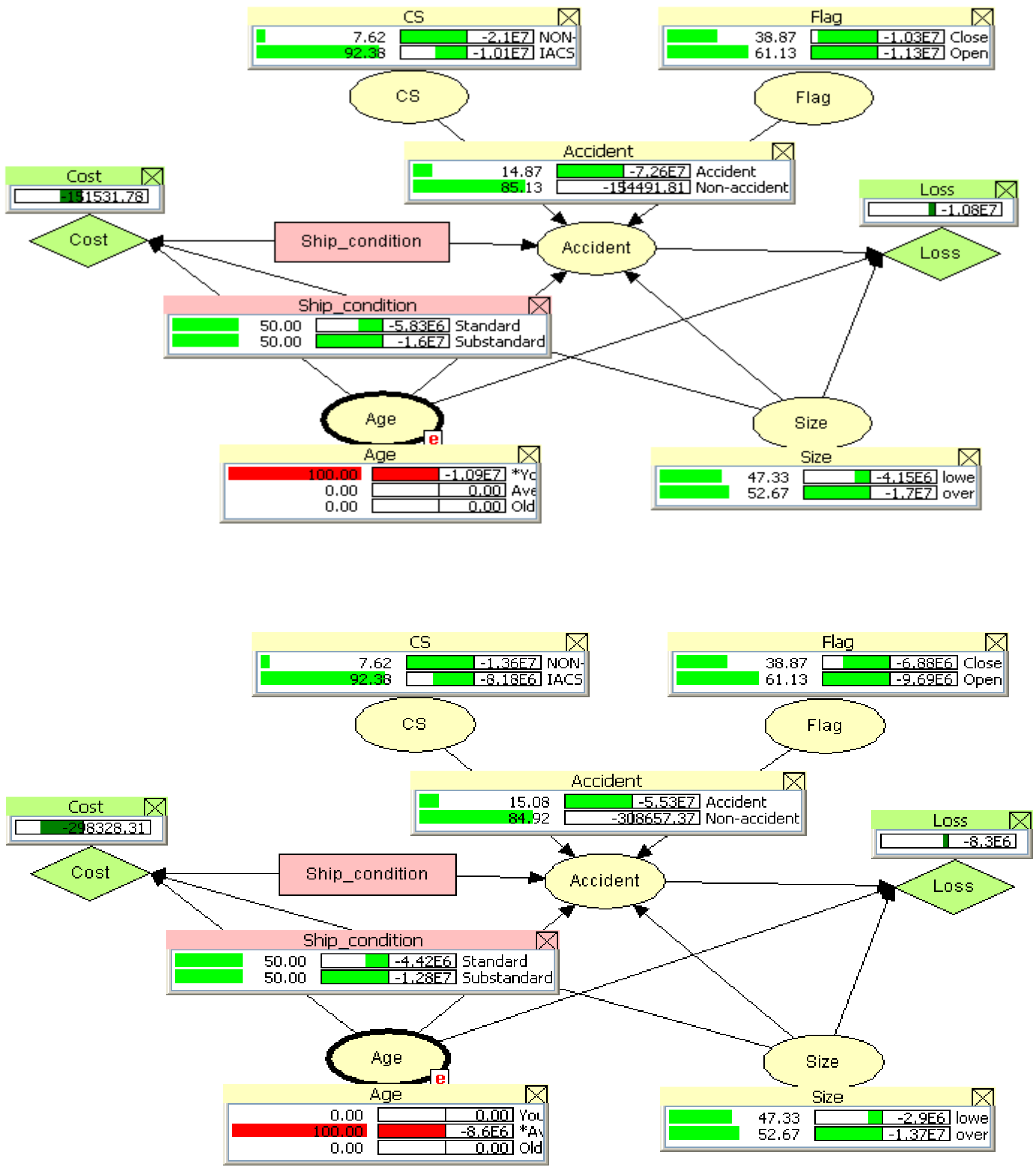
Table 6-14: The expect accident loss under different vessel size (\$M)

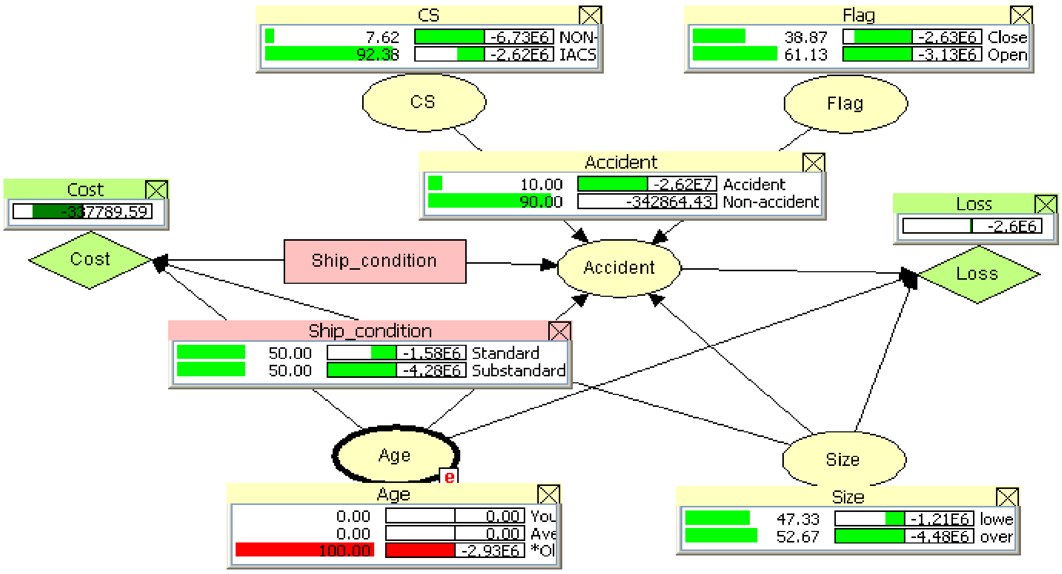
Type	Lower			Over			Different (%)
	M&R cost	Loss	Total	M&R cost	Loss	Total	
Container	0.21	2.76	2.97	0.26	12.00	12.26	312.74
Dry Cargo	0.24	0.47	0.71	0.28	1.62	1.90	168.07
Bulk	0.24	2.92	3.16	0.38	7.89	8.27	161.86
Tanker	0.49	0.57	1.05	0.48	6.57	7.05	570.99

6.2.5 The effect of vessel age

The results of this model suggest that an increase in vessel age contributes to a decrease in the probability of accident. In Figure 6-7 it can be observed that the accident probabilities of new, medium and old vessels will be 14.87%, 15.08% and 10% respectively.

Figure 6-7: The effect of vessel age (containerships)





The sensitivity analysis results of the five vessel types are shown in Table 6-15. The changes to the posterior probabilities are clearly shown when evidence changes from a new ship to an old ship. The average change of the five vessel types is 34.77%. The largest change among them is passenger ships (49.37%), followed by dry cargo ships (38.08%). The least affected by the factor of vessel age is containerships (5.25%).

Table 6-15: The effect of vessel age

Type	Prior probabilities	Posterior probabilities		
		VA1	VA2	VA3
Container	13.24	14.87	15.08	10
Dry Cargo	13.41	18.12	14.17	11.22
Bulk	12.91	14.48	12.95	9.39
Tanker	8.74	9.61	9.28	7.11
Passenger	9.25	12.68	11.96	6.42

Table 6-16 shows the expected loss for the different vessel age. The expected loss of a new container ship is $10.80M, and the cost of maintaining a new containership is $0.15M, so the expected overall cost to the shipowner is $10.955M. However, with regard to an old container ship, the expected loss for the accident is $2.60M, and the cost of maintaining is $0.34M, The expected overall cost to the shipowner is therefore $2.94M, which is a significant decrease compared to the new containership, which due to the old ships have a lower probability of accident.

The overall cost of a new bulk carrier is $8.36M, which is higher than an old one ($2.08M). Dry cargo and tanker ship have similar results. We can therefore conclude that the expected overall cost of an old ship is lower than that new ship.

Table 6-16: The expect accident loss under different vessel age ($M)

Type	New			Average			Old		
	M&R cost	Loss	Total	M&R cost	Loss	Total	M&R cost	Loss	Total
Container	0.15	10.80	10.95	0.30	8.30	8.60	0.34	2.60	2.94
Dry Cargo	0.14	3.02	3.16	0.27	0.64	0.91	0.31	0.39	0.69
Bulk	0.22	8.14	8.36	0.43	5.59	6.02	0.49	1.59	2.08
Tanker	0.38	5.82	6.20	0.75	2.62	3.37	0.49	0.20	0.68

6.2.6 The effect of vessel type

Vessel type determines the vessel's function in seaborne transportation, and principally affects the possibility of a certain vessel potentially suffering a particular type of maritime peril.

Table 6-17: The effect of vessel type

Type	Prior probabilities
Container	13.24
Dry Cargo	13.41
Bulk	12.91
Tanker	8.74
Passenger	9.25

Table 6-17 reveals that the probabilities of accidents occurring vary among different vessel type groups. Dry cargo ships have the largest accident probability, followed by containerships. Dry cargo ships are therefore those most liable in terms of accident occurrence, followed by containerships. Tanker ships have the lowest accident probability.

6.2.7 Discussion of the results obtained and validation of the model

From Tables 6-7 to 6-17 it can be concluded that the ship's condition is the largest single influencing factor on ship accident occurrence. The average change between posterior probabilities is 142.35%. The next factor is the classification society. The average change between posterior probabilities is 103.95%. Clearly, for different ship types such influencing factors have different levels of impact on possible accident occurrence. The age of a ship does not really influence the level of accident occurrence probability as much as the four factors above do, and actually the accident occurrence probability of a ship decreases slightly with the age of the vessel. This may appear to be arguable at first glance. However, this finding is reasonable in the sense that as times goes by greater experience and knowledge is obtained by the operators as they manage the ship, thus reducing the likelihood of any possible accident occurrence.

Model validation is possibly the most important step in the model building process, as it provides confidence in the results of the model. The two axioms described in Section 3.4 must be satisfied.

Table 6-18: Sensitivity analysis

Type	Prior probabilities	Substandard	Non-IACS	Open registered	Over size	New ship
	P(A=A1)	P(A=A1|SE=SE2)	P(A=A1|SE=SE2, CS=CS2)	P(A=A1|SE=SE2, CS=CS2,FS=FS1)	P(A=A1|SE=SE2, CS=CS2,FS=FS1, VS=VS2)	P(A=A1|SE=SE2, CS=CS2,FS=FS1,VS=VS2, VA=VA1)
Container	13.24	20.04	30.28	34.63	43.76	52.41
Dry Cargo	13.41	18	21.22	24.77	30.16	41.33
Bulk	12.91	18.71	29.59	31.02	35.33	39
Tanker	8.74	12.37	17.1	18.59	28.56	35.98
Passenger	9.25	12.13	14.67	14.9	18.67	27.17

Examination of the model, illustrated in Table 6-18, reveals that when the ship safety condition is set at 100% substandard, the accident probability increases from 13.24% to 20.04% for a containership. The third column in Table 13 illustrates that when SE=SE2 (i.e. 100% substandard) and CS=CS2 (i.e. 100% non-IACA member) are given, the accident probability is larger than when SE=SE2 is given. This analysis process continues, and consequently the values in the last column are larger than any value presented in the same row in Table 6-14. This is in harmony with Axiom 2 in Section 3.4, thus validating the model.

In this part, binary logistic regression method is used to provide the input for a BN, making use of different data resources detailing maritime accidents. By taking into account different actors (i.e. age, size etc.) and their mutual influences, maritime risk assessment using the BN enables identification of the factors that have the greatest impact on accident occurrence. We conclude that, although the maintenance cost for keeping a standard ship is higher, the expected overall cost is lower than that of a substandard ship. IACS members enforce strict regulations that reduce the occurrence probability of an accident of their vessels. There is a significant change in accident probability when vessels use open or closed registration. In terms of contributions to vessel accident occurrence probability, there is a significant difference between large and small ships, especially in the tanker section. The results of this model also suggest that an increase in vessel age is associated with a decrease in the probability of an accident.

Chapter 7：Strategic Maritime and Ships Inspection

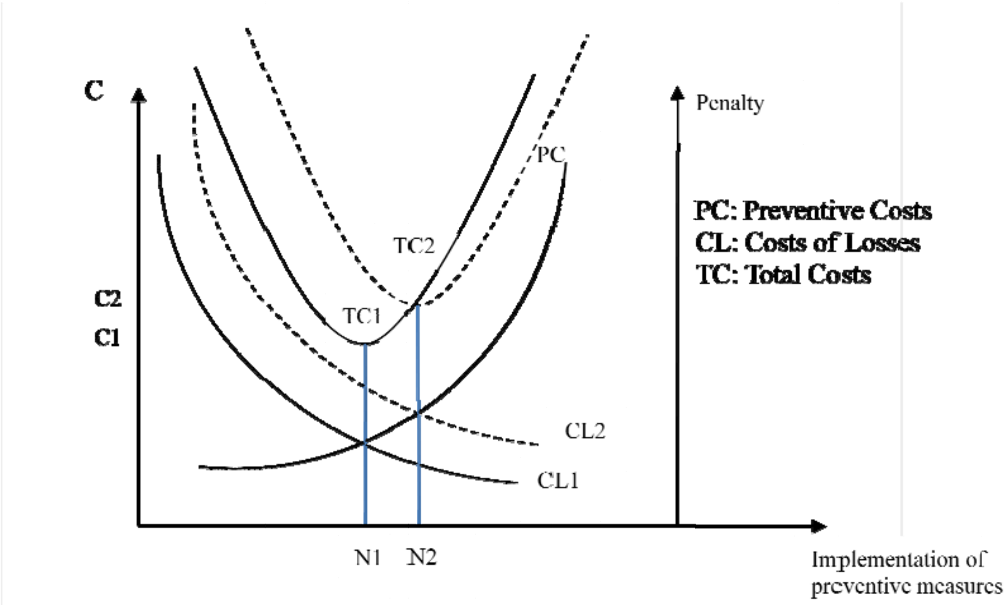
7.1 An inspection game and shipowner strategic choice

Safety analysis is implemented into the system in order to improve ship safety by reducing the inherent risks. The costs involved in implementing safety analysis can be regarded as preventive costs, which include safety equipment installation together with maintenance costs, staff training and so on.

On the other hand, the implementation of safety assessment also results in vessel accidents being made less likely, less severe, or a combination of the two. So the cost of any loss is also reduced.

The total safety cost, which is the sum of preventive costs and the cost of losses, can be used by the shipowner to find where the total cost is at its lowest. Such a cost optimization is illustrated in Figure7-1.

Figure 7-1: Optimal implementation of safety measures



The cost curve for preventive costs (PC) increases along with the implementation of preventive measures, whereas the curve for the cost of losses (CL) decreases with the increasing implementation of preventive measures. To the shipowner, point N1 is the optimal safety level, where the total cost is at its lowest.

However, the ports and maritime authorities think that a higher safety level is better. Maritime authorities hope that certain safety regulations, such as the Port State Control program, will push shipowners into implementing even more preventive measures for improving their ships' safety levels. The right part of N1 is expected by the safety authorities.

The delay caused by inspection could be strong enough to deter further violations, or the threat of a fine imposed on the violators could force shipowners to engage in self-correction before sending their ships to sea. The cost curve for the cost of losses (CL2) in figure 7-1 is the costs lost through an accident and the cost of penalties. The total costs curve changes to TC2. The optimal safety level changes to N2, and the shipowners' total cost increases to C2.

However, a shipowner's total cost will then be higher than their optimal total cost, so some shippers may turn to other destinations that have a more relaxed inspection policy, which will harm the competitiveness of a port.

For maritime authorities, a point more to the right does not mean it's a better point. Their limited resources, including both funding and human resources, restrict the amount of inspection possible. Generally, the MOU's funds are provided by each member and the inspection costs are borne by them. The MOU cannot and could not charge the shipowners or the ports. However, their costs increase along with the inspection rate, and the port state needs to get funds from other finance channels. IMO suggests that shipowners and ports should share part of the costs. There are a large number of ships calling at a port every day, but the port authority has limited human resources for taking charge of on-board inspections. For example, at Hong Kong port the authority has only six officers to inspect nearly 100 ships per day, so it is not realistic to check every ship.

Furthermore, excessive controls, increasing delays, tied-up capacities, inventory costs etc., may also be translated into costs paid ultimately by customers (Goss, 1989). So the port state has to face this conflict of internal interests, especially those ports that play the role of the main terminals in international trade.

There should be a point of equilibrium between the authorities and the shipowners. Hence, policies regarding port and maritime controls and inspections are strategic. The authorities require a balanced policy that assesses its economic implications and ensures only rational losses, accounting for both the need of controls and the handling of potential accidents. The overall aim of the port authorities is to construct an optimal inspection policy combined with punishments and fines in order to enable maritime authorities to deploy minimum resources that achieves minimum social welfare loss and one that also motivates shipowners to implement better safety maintenance policies.

In this part, these issues are assessed through empirical evidence regarding maritime security and ship inspection management. The research is embedded in a theoretical framework that recognizes the many parties involved in such inspections, along with their economic interests.

7.1.1 Two types of errors in Bi-Matrix game

Each strategy pair "ij" used by the port controller and by the shipowner has both risk and cost consequences. Let $\alpha_{ij}, \beta_{\mathrm{ij}}$ be two types of risks that are borne by the controller. The first type of risk α_{ij}, is a type I risk which is the probability that the controller has taken a strategy and reached a decision, but the ship is found non-conforming to regulatory constraints when in fact it is conforming. Such an error can occur because controls can be subject to errors. By the same token, the second type of error β_{ij}, called type II error, is an error that is made by the controller when inspection of the ship finds it conforming to acceptable standards when in fact it is not. For example, say that there are K regulatory constraints, and say that only a subset of such regulations is inspected and found to be conforming when in fact there are other, potentially more important regulations that are violated. Furthermore, some inspections are difficult to realize, as non-conformance might be no-transparent as well and therefore difficult to detect. Specific cases will subsequently be considered. These risks depend on one another—the actions of one determine the risks of the other. For simplicity, assume that x_i defines the probability that a control strategy is selected by the controller while the shipowner selects strategy j (mostly preventive) with a probability y_j. As a result, the resulting average type I and II risks that the port authority faces is$(\bar{\alpha}, \bar{\beta})$ which is constrained by the regulatory authorities.

$$\sum_{j=1}^{m}\sum_{i=1}^{n} x_i y_j \alpha_{ij} \leq \bar{\alpha}\,, \sum_{j=1}^{m}\sum_{i=1}^{n} x_i y_j \beta_{ij} \leq \bar{\beta}$$

where $\sum_{i=1}^{n} x_i = 1, \sum_{j=1}^{m} y_j = 1, 0 \leq x_i \leq 1{,}0 \leq y_j \leq 1.$

These probabilities are explicitly given by $\alpha_{PA}(j)$ and $\beta_{PA}(j)$ which are a function of the preventive measures assumed by the shipowner. The efforts are expressed by E for a high intensity effort and e for a low intensity effort. Again for simplicity, say that a vessel inspection consists of inspecting two regulations only and let $f(0,0)$ be the probability that no violation is found. As a result, the probability of finding at least one violation is $1 - f(0,0)$. In a statistical sense, v_{kj}were defined as the probability that a regulation k $(k = 1,2)$ is detected when an effort j is made by the vessel owner. If these are independent, the probability of detection given by

$$\prod_{k=1,2} v_{kj}^{z_k}\left(1 - v_{kj}^{z_k}\right), z_k = 0, 1$$

Or explicitly, the probability of a regulation violation is$1 - f(0,0) = 1 - (1 - v_{1j})(1 - v_{2j})$. If the vessel owner (mading a high effort $E\ or\ j = 1$) has attended to both regulations then clearly, $1 - f(0,0) = 1 - (1 - v_{1E})(1 - v_{2E})$ is a type I error corresponding to:

$$\alpha_{PA,1,E} = 1 - f_{1,E}(0,0) = 1 - (1 - v_{1E})(1 - v_{2E}), \beta_{PA,1,E} = 0$$

While the probability of a control accepting the vessel as fit when it is not is null as expressed above. However, if the vessel owner has not attended to both characteristics, the probability of making a type I error is null while the probability of making an error of the second kind is:

$$\alpha_{PA,1,e} = 0, \beta_{PA,1,e} = f_{1,e}(0,0) = (1 - v_{1e})(1 - v_{2e})$$

Finally, if the port authority makes no control, $\alpha_{PA,2,e} = 0$ as the controller cannot reject an inspection when it is good. However it will always accept the inspection whether it is good or bad. In such cases:

$$\alpha_{PA,2,E} = 0, \beta_{PA,2,E} = 0 \; and \; \alpha_{PA,2,e} = 0, \beta_{PA,2,e} = 1$$

For the regulator, presuming a vessel is compliant (with probability y) or not compliant (with probability $1 - y$), a controller inspecting a vessel with probability x and not inspecting with probability 1-x, an average type I and II error will be given by:

$$xy\alpha_{PA,1,E} + x(1-y)\alpha_{PA,1,e} + (1-x)y\alpha_{PA,2,E} + (1-x)(1-y)\alpha_{PA,2,e} \leq \bar{\alpha}$$

$$xy\beta_{PA,1,E} + x(1-y)\beta_{PA,1,e} + (1-x)y\beta_{PA,2,E} + (1-x)(1-y)\beta_{PA,2,e} \leq \bar{\beta}$$

and explicitly,

$$xy(1-(1-v_{1E})(1-v_{2E})) + x(1-y)0 + (1-x)y0 + (1-x)(1-y)0 \leq \bar{\alpha}$$

$$xy0 + x(1-y)(1-v_{1e})(1-v_{2e}) + (1-x)y0 + (1-x)(1-y)1 \leq \bar{\beta}$$

This is reduced to:

$$xy(1-(1-v_{1E})(1-v_{2E})) \leq \bar{\alpha}$$

$$x(1-y)(1-v_{1e})(1-v_{2e}) + (1-x)(1-y) \leq \bar{\beta}$$

Assume that the regulator risk specifications are maintained at equality, then the type I and II errors will dictate the propensity of both the Port authority to inspect and the shipowner to choose to invest in a larger effort: (probability y). These are given by a solution of $(x \in [0,1], y \in [0,1])$.

$$xy \leq \frac{\bar{\alpha}}{1-(1-v_{1E})(1-v_{2E})}$$

$$1-y-x\big(1-(1-v_{1e})(1-v_{2e})\big) \leq \bar{\beta} - \frac{\bar{\alpha}(1-v_{1e})(1-v_{2e})}{1-(1-v_{1E})(1-v_{2E})}$$

In other words, in the solution of the "game that the port authority and the shipowner play", the controller will select a control strategy to which the shipowner will have to respond in a manner in which the regulator's constraint is met. For example, if the port authority fully inspects every ship then x=1 and therefore:

$$1-\bar{\beta}-\big(1-(1-v_{1e})(1-v_{2e})\big)(1-\frac{\bar{\alpha}}{1-(1-v_{1E})(1-v_{2E})}) \leq y$$
$$\leq \frac{\bar{\alpha}}{1-(1-v_{1E})(1-v_{2E})}$$

Generally, for any x:

$$1-\bar{\beta}-\big(1-(1-v_{1e})(1-v_{2e})\big)(x-\frac{\bar{\alpha}}{1-(1-v_{1E})(1-v_{2E})}) \leq y$$
$$\leq \frac{1}{x}(\frac{\bar{\alpha}}{1-(1-v_{1E})(1-v_{2E})})$$

These constrains will be used subsequently in determining a solution to a game that is yet to be formulated.

7.1.2 The Matrix costs payoffs

Assume here that a vessel has one representative characteristic that the port authority may or may not attend to. Furthermore, the decision to control a vessel incurs a cost of C_p to the Port Authority while it incurs a cost of C_{sc} to the shipowner being controlled. If the vessel is found to be in violation of the characteristic being controlled, a penalty is imposed on the shipowner who pays a fine of F.

However, in practice, the main punishment to violating shipowners is detention, not a punitive penalty. In this study, the fine is assumed to exist, and the effects of the fine were analyzed in relation to the strategic.

Thus, a fine is paid by the shipowner when he is compliant in probability and an error of type I is made and which equals $1-\alpha_{PA,1,E}$ or when the shipowner is not compliant and is detected, which has a probability of $1-\beta_{PA,1,e}$. Of course, if the port authority chooses not to control a vessel, no control costs are assumed and no potential fines are collected.

In both cases, however, an accident may in probability occur in the port, depending on the care and effort the shipowner has made. In this case, $p_j, j=E,e$ are the probabilities of a vessel having an accident, with a consequential cost that will be defined by some random variable Ω_j. In this sense, a port authority can affect the probability of an accident through the incentives it imparts to the shipowner to take greater care of his ship. It cannot affect the magnitude and the effects of an accident once it has occurred, however. By the same token, consider now the shipowner who has two strategic alternatives-to attend to the vessel's compliance with regulatory standards, or simply not do so. If the shipowner is compliant, an effort E is imparted, while if it chooses not to be compliant a smaller effort is imparted, each of which may lead the controller to two types of errors. In this case:

$$\Omega_{E\ or\ e} = \begin{cases} \Xi & wp\ \ p_j \\ 0 & wp\ \ 1 - p_j \end{cases} \quad j = E, e$$

When the ship is inspected, a direct cost of C_{sc} is assumed by the shipowner due to the vessel's idleness, as well as related costs associated with maintenance and other charges. In addition, the shipowner sustains technology operational and preventive (compliance related) costs which summarized by $C(p_j, j)$, where $p_j, j = E, e$ is expressing the probability of an accident occurring, this also being a function of the effort put forth in preventive and compliance measures required by the port authority. The various costs sustained by the port authority and the shipowner are summarized in Table 1 below. Finally, the consequential costs of an accident, for simplicity, being a function of the probability $p_j, j = E, e$, are determined by both the technology used by the vessel (its type, design, etc.) and by the effort it makes in attending to compliance standards.

This expression is also specified in the random costs matrix in Table 1 and is used to highlight the costs that are sustained through an accident. The treatment of this cost is an important part of the "tools" that regulators use in setting their risk constraints. Furthermore, the cost of the port authority controls are necessarily a function of the errors (Types I and II) they are willing to sustain, thus, implying that

$$C_p = C_p(\alpha_{PA}(j), \beta_{PA}(j).$$

When an accident happens, there will be some pollution damage and cleanup or recovery costs. In this case, the damage and the restoration costs can reflect social welfare losses. The government should consider these losses as part of the costs. In this game, the port authority optimizes social welfare as the chief target (Florens and Foucher, 1999), but at the same time the inspection costs should also be taken into account.

$D(j)$was set as the pollution damage function and $C(j)$ as the cleanup or recovery cost function. Here it is presumed that all pollution is cleaned up, which may not be socially optimal if the cleanup technology is expensive. $\big(D(j) + C(j)\big)p(j)$ are thus the expected social loss of the accident given the effort j and $p_j, j = E, e$ are the probabilities of the vessel having an accident.

Table 7-1: The matrix costs payoffs

	Hi Intensity Prevention	**Low Intensity Prevention**
Port Authority Exercises a Control	$\begin{pmatrix} \begin{cases} D(E)+C(E) & wp\ \ p_E \\ 0 & wp\ \ 1-p_E \end{cases} + C_p + \begin{cases} -F & wp\ \ \alpha_{PA,1,E} \\ 0 & wp\ \ 1-\alpha_{PA,1,E} \end{cases} \\ C_{SC} + C(P_E, E) + \begin{cases} F & wp\ \ \alpha_{PA,1,E} \\ 0 & wp\ \ 1-\alpha_{PA,1,E} \end{cases} + \begin{cases} \Omega_E & wp\ \ p_E \\ 0 & wp\ \ 1-p_E \end{cases} \end{pmatrix}$	$\begin{pmatrix} \begin{cases} D(e)+C(e) & wp\ \ p_e \\ 0 & wp\ \ 1-p_e \end{cases} + C_p + \begin{cases} -F & wp\ \ \alpha_{PA,1,e} \\ 0 & wp\ \ 1-\alpha_{PA,1,e} \end{cases} \\ C_{SC} + C(P_e, e) + \begin{cases} F & wp\ \ \alpha_{PA,1,e} \\ 0 & wp\ \ 1-\alpha_{PA,1,e} \end{cases} + \begin{cases} \Omega_e & wp\ \ p_e \\ 0 & wp\ \ 1-p_e \end{cases} \end{pmatrix}$
No Controls	$\begin{pmatrix} \begin{cases} D(E)+C(E) & wp\ \ p_E \\ 0 & wp\ \ 1-p_E \end{cases} \\ C_{SC} + C(P_E, E) + \begin{cases} \Omega_E & wp\ \ p_E \\ 0 & wp\ \ 1-p_E \end{cases} \end{pmatrix}$	$\begin{pmatrix} \begin{cases} D(e)+C(e) & wp\ \ p_e \\ 0 & wp\ \ 1-p_e \end{cases} \\ C_{SC} + C(P_e, e) + \begin{cases} \Omega_e & wp\ \ p_e \\ 0 & wp\ \ 1-p_e \end{cases} \end{pmatrix}$

With the regulation risk constraints:

$$xy\alpha_{PA}(E) \leq \bar{\alpha} \;\; with \; \alpha_{PA}(E) = 1 - f_{1,E}(0,0) = 1 - (1 - v_{1E})(1 - v_{2E})$$

$$x(1-y)\beta_{PA}(e) + (1-x)(1-y) \leq \bar{\beta} \;\;\; with \; \beta_{PA}(e) = (1 - v_{1e})(1 - v_{2e})$$

or

$$1 - \bar{\beta} - \big(1 - (1 - v_{1e})(1 - v_{2e})\big)(x - \frac{\bar{\alpha}}{1 - (1 - v_{1E})(1 - v_{2E})}) \leq y \leq \frac{1}{x}(\frac{\bar{\alpha}}{1 - (1 - v_{1E})(1 - v_{2E})})$$

where (x, y) are the strategic choices open to the controller and to the shipowner.

The accidents damage in this case is given by $y\Omega_E + (1-y)\Omega_e$, while a value at risk quintile risk constraint is:

$$Prob(y\Omega_E + (1-y)\Omega_e \geq VaR) \leq \varepsilon$$

Or $Prob(y \leq \frac{\Omega_e - VaR}{\Omega_e - \Omega_E} \leq \varepsilon$

where $E(\gamma) = y\Xi_E\pi_E + (1-y)\Xi_e\pi_e$

$$VaR\,\gamma = \Xi^2(y\pi_E(1-\pi_E)\Xi_E^2 + (1-y)\pi_e(1-\pi_e)\Xi_e^2 - 2y(1-y)\pi_e\pi_E\Xi_E\Xi_e)$$

Of course, expected costs can be easily derived in this case and are given by the following bi-matrix (Table 2).

Table 7-2: Expected costs Bi-Matrix

	Hi Intensity Prevention	Low Intensity Prevention
Port Authority Exercises a Control	$\begin{pmatrix} \big(D(E)+C(E)\big)p_E + C_p - F\big(\alpha_{PA}(E)\big) \\ C_{SC} + C(p_E, E) + F\big(\alpha_{PA}(E)\big) + \Omega_E p_E \end{pmatrix}$	$\begin{pmatrix} \big(D(e)+C(e)\big)p_e + C_p - F\big(\alpha_{PA}(e)\big) \\ C_{SC} + C(p_e, e) + F\big(\alpha_{PA}(e)\big) + \Omega_e \end{pmatrix}$
No Controls	$\begin{pmatrix} \big(D(E)+C(E)\big)p_E \\ C(p_E, E) + \Omega_E p_E \end{pmatrix}$	$\begin{pmatrix} \big(D(e)+C(e)\big)p_e \\ C(p_e, e) + \Omega_e \end{pmatrix}$

The inspection problem is thus reduced, as stated above, to a simple deterministic bi-matrix game, with the risk constraints as defined above. The inspection game then has the following normal form. The set of strategies of the port authority is$(x, 1-x)$. The set of strategies of the shipowners is $(y, 1-y)$.

7.1.3 Port authorities' strategic choices

The payoffs to the port authority and shipowners are denoted as $P(x, y)$ and $S(x, y)$. In terms of the payoffs in table 2, the payoff function of the port authority is

$$\begin{aligned} P(x,y) = x[&\Big(\big(D(E)+C(E)\big)p_E + C_p - F\big(\alpha_{PA}(E)\big)\Big)y \\ &- (1-y)((D(e)+C(e))p_e + C_p - F\big(1-\beta_{PA}(e)\big)] \\ &+ (1-x)\Big[\big(D(E)+C(E)\big)p_E y + \Big(\big(D(e)+C(e)\big)p_e\Big)(1-y)\Big] \end{aligned}$$

$$= \left[F\big(1-\beta_{PA}(e)\big) - F\big(\alpha_{PA}(E)\big)\right]xy + \left[C_p - F\big(1-\beta_{PA}(e)\big)\right]x$$
$$+ \left[\big(D(E)+C(E)\big)p_E - \big(D(e)+C(e)\big)p_e\right]y + \big(D(e)+C(e)\big)p_e$$

$$S(x,y) = y\left[\big(C_{SC} + C(p_E,E) + F\big(\alpha_{PA}(E)\big) + \Omega_E p_E\big)x\right.$$
$$\left. + (C(p_E,E) + \Omega_E p_E)(1-x)\right]$$
$$+ (1-y)\left[\big(C_{SC} + C(p_e,e) + F\big(1-\beta_{PA}(e)\big) + \Omega_e p_e\big)x\right.$$
$$\left. + (C(p_e,e) + \Omega_e p_e)(1-x)\right]$$

$$= \left[F\big(\alpha_{PA}(E)\big) - F\big(1-\beta_{PA}(e)\big)\right]xy + \left[C_{SC} + F\big(1-\beta_{PA}(e)\big)\right]x$$
$$+ [(C(p_E,E) + \Omega_E p_E) - (C(p_e,e) + \Omega_e p_e)]y$$
$$+ (C(p_e,e) + \Omega_e p_e)$$

With the regulation risk constraints:

$$g_1(x) = xy\alpha_{PA}(E) - \bar{\alpha} \leq 0$$

$$g_2(x) = x(1-y)\beta_{PA}(e) + (1-x)(1-y) - \bar{\beta} \leq 0$$

where $\alpha_{PA}(E) = 1 - f_{1,E}(0,0) = 1 - (1-v_{1E})(1-v_{2E})$

$\beta_{PA}(e) = (1-v_{1e})(1-v_{2e})$

$g_1(x)$ can be rewritten as: $x \leq \frac{\bar{\alpha}}{\alpha_{PA}(E)}\frac{1}{y}$

$g_2(x)$ can be rewritten as: $x \geq \frac{\bar{\beta}-(1-y)}{(1-y)(\beta_{PA}(e)-1)}$

(1) If $\bar{\beta} - (1 - y) < 0$, it means $y < 1 - \bar{\beta}$

Then $x \geq \frac{\bar{\beta}-(1-y)}{(1-y)(\beta_{PA}(e)-1)} > 0$

So the regulation risk constraints are:

$$\frac{\bar{\beta} - (1 - y)}{(1 - y)(\beta_{PA}(e) - 1)} \leq x \leq \frac{\bar{\alpha}}{\alpha_{PA}(E)} \frac{1}{y}$$

A pair of mixed strategies $(\bar{x}, \bar{y})$ is the Nash equilibrium of this no cooperative game is looking for.

$$\bar{x}^T A \bar{y} \geq x^T \; for \; all \;\; x \in X$$

$$\bar{x}^T B \bar{y} \geq x^T \; for \; all \;\; y \in Y$$

Here, the constraints are inequality, so slack variables can be used to turn it into equality. In linear programming a slack variable is a variable which is added to a constraint to turn the inequality into an equation. It is required to turn an inequality into an equality where a linear combination of variables is less than or equal to a given constant in the former. With the other variables in the augmented constraints, the slack variable cannot take on negative values, as the simplex algorithm requires them to be positive or zero.

Assume a_1 and b_1 are two slack variables, and then the constraints can be rewrite as

$$h_1(x, a_1) = g_1(x) + a_1^2 = xy\alpha_{PA}(E) - \bar{\alpha} + a_1^2 = 0$$

$$h_2(x, b_1) = g_2(x) + b_1^2 = x(1-y)\beta_{PA}(e) + (1-x)(1-y) - \bar{\beta} + b_1^2 = 0$$

So, the Lagrangian function of this question is

$$F(x, a_1, b_1, \lambda_1, \lambda_2) = P(x, y) + \lambda_1 h_1(x, a_1, b_1) + \lambda_2 h_2(x, a_1, b_1)$$

$$= [F(1-\beta_{PA}(e)) - F(\alpha_{PA}(E))]xy + [C_p - F(1-\beta_{PA}(e))]x$$

$$+ [(D(E) + C(E))p_E - (D(e) + C(e))p_e]y + (D(e) + C(e))p_e$$

$$+ \lambda_1(xy\alpha_{PA}(E) - \bar{\alpha} + a_1^2) + \lambda_2(x(1-y)\beta_{PA}(e)$$

$$+ (1-x)(1-y) - \bar{\beta} + b_1^2)$$

$$\lambda_1 \geq 0, \lambda_2 \geq 0$$

With the Lagrange multiplier method, the condition of this problem is

$$\frac{\partial F}{\partial x} = \frac{\partial P}{\partial x} + \lambda_1 \frac{dg_1}{dx} + \lambda_2 \frac{dg_2}{dx}$$

$$= [F(1-\beta_{PA}(e)) - F(\alpha_{PA}(E))]y + [C_p - F(1-\beta_{PA}(e))]$$

$$+ \lambda_1(y\alpha_{PA}(E)) - \lambda_2 y\beta_{PA}(e) - \lambda_2 + \lambda_2 y = 0$$

$$\frac{\partial F}{\partial a_1} = 2\lambda_1 a_1 = 0$$

$$\frac{\partial F}{\partial b_1} = 2\lambda_1 b_1 = 0$$

$$\frac{\partial F}{\partial \lambda_1} = h_1(x, a_1) = g_1(x) + a_1^2 = xy\alpha_{PA}(E) - \bar{\alpha} + a_1^2 = 0$$

$$\frac{\partial F}{\partial \lambda_2} = h_2(x, b_1) = g_2(x) + b_1^2 = x(1-y)\beta_{PA}(e) + (1-x)(1-y) - \bar{\beta} + b_1^2 = 0$$

$$\lambda_1 a_1 = 0 \begin{cases} \lambda_1 = 0, a_1 \neq 0 & \Rightarrow g_1(x) = xy\alpha_{PA}(E) - \bar{\alpha} < 0 \\ \lambda_1 \geq 0, a_1 = 0 & \Rightarrow g_1(x) = xy\alpha_{PA}(E) - \bar{\alpha} = 0 \end{cases}$$

$$\lambda_1 b_1 = 0 \begin{cases} \lambda_2 = 0, b_1 \neq 0 & \Rightarrow g_2(x) = x(1-y)\beta_{PA}(e) + (1-x)(1-y) - \bar{\beta} < 0 \\ \lambda_2 \geq 0, b_1 = 0 & \Rightarrow g_2(x) = x(1-y)\beta_{PA}(e) + (1-x)(1-y) - \bar{\beta} = 0 \end{cases}$$

$$\begin{cases} \frac{\partial F}{\partial x} = \frac{\partial P}{\partial x} + \lambda_1 \frac{dg_1}{dx} + \lambda_2 \frac{dg_2}{dx} = 0 \\ \lambda_1 g_1(x) = 0 \\ \lambda_2 g_2(x) = 0 \\ \lambda_1 \geq 0 \\ \lambda_2 \geq 0 \end{cases}$$

This is Karush-Kuhn-Tucker Optimality Criteria.

There are three situations according to the position of x.

When $\frac{\bar{\beta}-(1-y)}{(1-y)(\beta_{PA}(e)-1)} < x < \frac{\bar{\alpha}}{\alpha_{PA}(E)}\frac{1}{y}$

Then $\lambda_1 = \lambda_2 = 0$, the Karush-Kuhn-Tucker Optimality Criteria is

$$\frac{\partial F}{\partial x} = \frac{\partial P}{\partial x} = 0$$

Then

$$\frac{\partial P}{\partial x} = \left[F\left(1 - \beta_{PA}(e)\right) - F\left(\alpha_{PA}(E)\right)\right]y + \left[C_p - F\left(1 - \beta_{PA}(e)\right)\right] = 0$$

So

$$Y=\frac{F\left(1-\beta_{PA}(e)\right)-C_p}{F\left(1-\beta_{PA}(e)\right)-F\left(\alpha_{PA}(E)\right)}$$

When $x=\frac{\bar{\beta}-(1-y)}{(1-y)(\beta_{PA}(e)-1)}, \lambda_1\geq 0, \lambda_2=0$, the Karush-Kuhn-Tucker Optimality Criteria is

$$\frac{\partial F}{\partial x}=\frac{\partial P}{\partial x}-\lambda_1=0$$

When $x=\frac{\bar{\alpha}}{\alpha_{PA}(E)}\frac{1}{y}, \lambda_1=0, \lambda_2\geq 0$, the Karush-Kuhn-Tucker Optimality Criteria is

$$\frac{\partial F}{\partial x}=\frac{\partial P}{\partial x}+\lambda_2=0$$

(2) If $\bar{\beta}-(1-y)\geq 0,$ it means $y\geq 1-\bar{\beta}$

Then $\frac{\bar{\beta}-(1-y)}{(1-y)(\beta_{PA}(e)-1)}\leq 0.$

So the regulation risk constraints are:

$$0\leq x\leq\frac{\bar{\alpha}}{\alpha_{PA}(E)}\frac{1}{y}$$

Assume c_1 is slack variable, then the constraints can be rewrite as

$$h_1(x,c_1)=g_1(x)+c_1^2=xy\alpha_{PA}(E)-\bar{\alpha}+c_1^2=0$$

So, the Lagrangian function of this question is

$$F(x, c_1, \lambda_1, \lambda_2) = P(x,y) + \lambda_1 h_1(x, c_1)$$

$$= \left[F\left(1-\beta_{PA}(e)\right) - F\left(\alpha_{PA}(E)\right)\right]xy + \left[C_p - F\left(1-\beta_{PA}(e)\right)\right]x$$

$$+ \left[\left(D(E)+C(E)\right)p_E - \left(D(e)+C(e)\right)p_e\right]y + \left(D(e)+C(e)\right)p_e$$

$$+ \lambda_1(xy\alpha_{PA}(E) - \bar{\alpha} + c_1^2)$$

$$\lambda_1 \geq 0,$$

With the Lagrange multiplier method, the condition of this problem is

$$\frac{\partial F}{\partial x} = \frac{\partial P}{\partial x} + \lambda_1 \frac{dg_1}{dx}$$

$$= \left[F\left(1-\beta_{PA}(e)\right) - F\left(\alpha_{PA}(E)\right)\right]y + \left[C_p - F\left(1-\beta_{PA}(e)\right)\right]$$

$$+ \lambda_1\left(y\alpha_{PA}(E)\right) = 0$$

$$\frac{\partial F}{\partial c_1} = 2\lambda_1 c_1 = 0$$

$$\frac{\partial F}{\partial \lambda_1} = h_1(x, c_1) = g_1(x) + c_1^2 = xy\alpha_{PA}(E) - \bar{\alpha} + c_1^2 = 0$$

$$\frac{\partial F}{\partial \lambda_2} = h_2(x, b_1) = g_2(x) + b_1^2 = x(1-y)\beta_{PA}(e) + (1-x)(1-y) - \bar{\beta} + b_1^2$$
$$= 0$$

$$\lambda_1 c_1 = 0 \begin{cases} \lambda_1 = 0, c_1 \neq 0 & \Rightarrow g_1(x) = xy\alpha_{PA}(E) - \bar{\alpha} < 0 \\ \lambda_1 \geq 0, c_1 = 0 & \Rightarrow g_1(x) = xy\alpha_{PA}(E) - \bar{\alpha} = 0 \end{cases}$$

$$\begin{cases} \dfrac{\partial F}{\partial x} = \dfrac{\partial P}{\partial x} + \lambda_1 \dfrac{dg_1}{dx} = 0 \\ \lambda_1 g_1(x) = 0 \\ \lambda_1 \geq 0 \end{cases}$$

This is Karush-Kuhn-Tucker Optimality Criteria.

There are two situations according to the position of x.

When $0 < x < \frac{\bar{\alpha}}{\alpha_{PA}(E)}\frac{1}{y}$

Then $\lambda_1 = 0$, the Karush-Kuhn-Tucker Optimality Criteria is

$$\frac{\partial F}{\partial x} = \frac{\partial P}{\partial x} = 0$$

$$\frac{\partial P}{\partial x} = \left[F\big(1-\beta_{PA}(e)\big) - F\big(\alpha_{PA}(E)\big)\right]y + \left[C_p - F\big(1-\beta_{PA}(e)\big)\right] = 0$$

So

$$Y = \frac{F\big(1-\beta_{PA}(e)\big) - C_p}{F\big(1-\beta_{PA}(e)\big) - F\big(\alpha_{PA}(E)\big)}$$

When $x = \frac{\bar{\beta}-(1-y)}{(1-y)(\beta_{PA}(e)-1)}, \lambda_1 \geq 0$, the Karush-Kuhn-Tucker Optimality Criteria is

$$\frac{\partial F}{\partial x} = \frac{\partial P}{\partial x} + \lambda_1 = 0$$

When $x = \frac{\bar{\alpha}}{\alpha_{PA}(E)}\frac{1}{y}, \lambda_1 = 0, \lambda_2 \geq 0$, the Karush-Kuhn-Tucker Optimality Criteria is

$$\frac{\partial F}{\partial x} = \frac{\partial P}{\partial x} + \lambda_2 = 0$$

7.1.4 Shipowner's strategic choice

In terms of the payoffs in table 2, the payoff function of shipowner is

$$S(x,y) = y\big[\big(C_{SC} + C(p_E,E) + F\big(\alpha_{PA}(E)\big) + \Omega_E p_E\big)x$$

$$+ (C(p_E,E) + \Omega_E p_E)(1-x)\big]$$

$$+ (1-y)\big[\big(C_{SC} + C(p_e,e) + F\big(1-\beta_{PA}(e)\big) + \Omega_e p_e\big)x$$

$$+ (C(p_e,e) + \Omega_e p_e)(1-x)\big]$$

$$= \big[F\big(\alpha_{PA}(E)\big) - F\big(1-\beta_{PA}(e)\big)\big]xy + \big[C_{SC} + F\big(1-\beta_{PA}(e)\big)\big]x$$

$$+ [(C(p_E,E) + \Omega_E p_E) - (C(p_e,e) + \Omega_e p_e)]y$$

$$+ (C(p_e,e) + \Omega_e p_e)$$

With the regulation risk constraints:

$$g_1(x) = xy\alpha_{PA}(E) - \bar{\alpha} \le 0$$

$$g_2(x) = x(1-y)\beta_{PA}(e) + (1-x)(1-y) - \bar{\beta} \le 0$$

where $\alpha_{PA}(E) = 1 - f_{1,E}(0,0) = 1 - (1-v_{1E})(1-v_{2E})$

$$\beta_{PA}(e) = (1-v_{1e})(1-v_{2e})$$

$g_1(y)$ can be rewrite as: $y \le \frac{\bar{\alpha}}{\alpha_{PA}(E)}\frac{1}{x}$

$g_2(y)$ can be rewrite as: $y \ge 1 - \frac{\bar{\beta}}{x\beta_{PA}(e)+(1-x)}$

(1) If $1-\frac{\bar{\beta}}{x\beta_{PA}(e)+(1-x)}>0$, it means $x<\frac{1-\bar{\beta}}{1-\beta_{PA}(e)}$

Then $y\geq 1-\frac{\bar{\beta}}{x\beta_{PA}(e)+(1-x)}>0$

So the regulation risk constraints are:

$$1-\frac{\bar{\beta}}{x\beta_{PA}(e)+(1-x)}\leq y\leq \frac{\bar{\alpha}}{\alpha_{PA}(E)}\frac{1}{x}$$

Assume $a_1$and b_1 are two slack variables, then the constraints can be rewrite as

$$h_1(y,a_1)=g_1(y)+a_1^2=xy\alpha_{PA}(E)-\bar{\alpha}+a_1^2=0$$

$$h_2(y,b_1)=g_2(y)+b_1^2=x(1-y)\beta_{PA}(e)+(1-x)(1-y)-\bar{\beta}+b_1^2=0$$

So, the Lagrangian function of this question is

$$\begin{aligned}F(y,a_1,b_1,\lambda_1,\lambda_2)&=S(x,y)+\mu_1h_1(x,a_1,b_1)+\mu_2h_2(x,a_1,b_1)\\&=\left[F\left(\alpha_{PA}(E)\right)-F\left(1-\beta_{PA}(e)\right)\right]xy+\left[C_{SC}+F\left(1-\beta_{PA}(e)\right)\right]x\\&+[(C(p_E,E)+\Omega_Ep_E)-(C(p_e,e)+\Omega_ep_e)]y\\&+(C(p_e,e)+\Omega_ep_e)+\mu_1(xy\alpha_{PA}(E)-\bar{\alpha}+a_1^2)\\&+\mu_2(x(1-y)\beta_{PA}(e)+(1-x)(1-y)-\bar{\beta}+b_1^2)\end{aligned}$$

$$\mu_1\geq 0,\mu_2\geq 0$$

With the Lagrange multiplier method, the condition of this problem is

$$\frac{\partial F}{\partial y} = \frac{\partial P}{\partial y} + \mu_1 \frac{dg_1}{dy} + \mu_2 \frac{dg_2}{dy}$$

$$= \left[F\left(\alpha_{PA}(E)\right) - F\left(1 - \beta_{PA}(e)\right)\right]x$$

$$+ \left[\left(C(p_E, E) + \Omega_E p_E\right) - \left(C(p_e, e) + \Omega_e p_e\right)\right] + \mu_1\left(x\alpha_{PA}(E)\right)$$

$$- \mu_2[x\beta_{PA}(e) - 1 + x] = 0$$

$$\frac{\partial F}{\partial a_1} = 2\mu_1 a_1 = 0$$

$$\frac{\partial F}{\partial b_1} = 2\mu_1 b_1 = 0$$

$$\frac{\partial F}{\partial \mu_1} = h_1(y, a_1) = g_1(y) + a_1^2 = xy\alpha_{PA}(E) - \bar{\alpha} + a_1^2 = 0$$

$$\frac{\partial F}{\partial \mu_2} = h_2(y, b_1) = g_2(y) + b_1^2 = x(1-y)\beta_{PA}(e) + (1-x)(1-y) - \bar{\beta} + b_1^2 = 0$$

$$\mu_1 a_1 = 0 \begin{cases} \mu_1 = 0, a_1 \neq 0 & \Rightarrow g_1(x) = xy\alpha_{PA}(E) - \bar{\alpha} < 0 \\ \mu_1 \geq 0, a_1 = 0 & \Rightarrow g_1(x) = xy\alpha_{PA}(E) - \bar{\alpha} = 0 \end{cases}$$

$$\mu_1 b_1 = 0 \begin{cases} \mu_2 = 0, b_1 \neq 0 & \Rightarrow g_2(x) = x(1-y)\beta_{PA}(e) + (1-x)(1-y) - \bar{\beta} < 0 \\ \mu_2 \geq 0, b_1 = 0 & \Rightarrow g_2(x) = x(1-y)\beta_{PA}(e) + (1-x)(1-y) - \bar{\beta} = 0 \end{cases}$$

$$\begin{cases} \frac{\partial F}{\partial y} = \frac{\partial P}{\partial y} + \mu_1 \frac{dg_1}{dy} + \mu_2 \frac{dg_2}{dy} = 0 \\ \mu_1 g_1(y) = 0 \\ \mu_2 g_2(y) = 0 \\ \mu_1 \geq 0 \\ \mu_2 \geq 0 \end{cases}$$

This is Karush-Kuhn-Tucker Optimality Criteria.

There are three situations according to the position of y.

When $1-\frac{\bar{\beta}}{x\beta_{PA}(e)+(1-x)}<y<\frac{\bar{\alpha}}{\alpha_{PA}(E)}\frac{1}{x}$

Then $\mu_1=\mu_2=0$, the Karush-Kuhn-Tucker Optimality Criteria is

$$\frac{\partial F}{\partial y}=\frac{\partial S}{\partial y}=0$$

Then

$$\frac{\partial S}{\partial y}=\left[F\left(\alpha_{PA}(E)\right)-F\left(1-\beta_{PA}(e)\right)\right]x$$
$$+\left[\left(C(p_E,E)+\Omega_E p_E\right)-\left(C(p_e,e)+\Omega_e p_e\right)\right]=0$$

So

$$X=\frac{\left(C(p_E,E)+\Omega_E p_E\right)-\left(C(p_e,e)+\Omega_e p_e\right)}{F\left(\alpha_{PA}(E)\right)-F\left(1-\beta_{PA}(e)\right)}$$

When $y=1-\frac{\bar{\beta}}{x\beta_{PA}(e)+(1-x)},\mu_1\geq 0,\mu_2=0$, the Karush-Kuhn-Tucker Optimality Criteria is

$$\frac{\partial F}{\partial y}=\frac{\partial S}{\partial y}-\mu_1=0$$

When $y=\frac{\bar{\alpha}}{\alpha_{PA}(E)}\frac{1}{x},\mu_1=0,\mu_2\geq 0$, the Karush-Kuhn-Tucker Optimality Criteria is

$$\frac{\partial F}{\partial y}=\frac{\partial S}{\partial y}+\mu_2=0$$

(2) If $1-\frac{\overline{\beta}}{x\beta_{PA}(e)+(1-x)} \leq 0$, it means $x \geq \frac{1-\overline{\beta}}{1-\beta_{PA}(e)}$

So the regulation risk constraints are:

$$0 \leq y \leq \frac{\bar{\alpha}}{\alpha_{PA}(E)} \frac{1}{x}$$

Assume $c_1$is slack variables, then the constraints can be rewrite as

$$h_1(y, c_1) = g_1(y) + c_1^2 = xy\alpha_{PA}(E) - \bar{\alpha} + c_1^2 = 0$$

So, the Lagrangian function of this question is

$$\begin{aligned} F(y, c_1, \mu_1, \mu_2) &= S(x, y) + \mu_1 h_1(y, c_1) \\ &= \left[F\left(\alpha_{PA}(E)\right) - F\left(1-\beta_{PA}(e)\right)\right]xy + \left[C_{SC} + F\left(1-\beta_{PA}(e)\right)\right]x \\ &+ [(C(p_E, E) + \Omega_E p_E) - (C(p_e, e) + \Omega_e p_e)]y \\ &+ (C(p_e, e) + \Omega_e p_e) + \mu_1(xy\alpha_{PA}(E) - \bar{\alpha} + c_1^2) \end{aligned}$$

$$\mu_1 \geq 0$$

With the Lagrange multiplier method, the condition of this problem is

$$\begin{aligned} \frac{\partial F}{\partial y} &= \frac{\partial P}{\partial y} + \mu_1 \frac{dg_1}{dy} \\ &= \left[F\left(\alpha_{PA}(E)\right) - F\left(1-\beta_{PA}(e)\right)\right]x \\ &+ [(C(p_E, E) + \Omega_E p_E) - (C(p_e, e) + \Omega_e p_e)] + \mu_1\left(x\alpha_{PA}(E)\right) \end{aligned}$$

$$\frac{\partial F}{\partial c_1} = 2\mu_1 c_1 = 0$$

$$\frac{\partial F}{\partial \mu_1} = h_1(y, c_1) = g_1(y) + c_1^2 = xy\alpha_{PA}(E) - \bar{\alpha} + c_1^2 = 0$$

$$\mu_1 c_1 = 0 \begin{cases} \mu_1 = 0, c_1 \neq 0 & \Rightarrow g_1(x) = xy\alpha_{PA}(E) - \bar{\alpha} < 0 \\ \mu_1 \geq 0, c_1 = 0 & \Rightarrow g_1(x) = xy\alpha_{PA}(E) - \bar{\alpha} = 0 \end{cases}$$

$$\begin{cases} \frac{\partial F}{\partial y} = \frac{\partial P}{\partial y} + \mu_1 \frac{dg_1}{dy} = 0 \\ \mu_1 g_1(y) = 0 \\ \mu_1 \geq 0 \end{cases}$$

This is Karush-Kuhn-Tucker Optimality Criteria.

There are three situations according to the position of y.

When $0 < y < \frac{\bar{\alpha}}{\alpha_{PA}(E)} \frac{1}{x}$

Then $\mu_1 =$, the Karush-Kuhn-Tucker Optimality Criteria is

$$\frac{\partial F}{\partial y} = \frac{\partial S}{\partial y} = 0$$

Then

$$\frac{\partial S}{\partial y} = \left[F\left(\alpha_{PA}(E)\right) - F\left(1 - \beta_{PA}(e)\right)\right]x$$
$$+ [(C(p_E, E) + \Omega_E p_E) - (C(p_e, e) + \Omega_e p_e)] = 0$$

So

$$X = \frac{(C(p_E, E) + \Omega_E p_E) - (C(p_e, e) + \Omega_e p_e)}{F(\alpha_{PA}(E)) - F(1 - \beta_{PA}(e))}$$

When $y = \frac{\bar{\alpha}}{\alpha_{PA}(E)} \frac{1}{x}, \mu_1 \geq 0$, the Karush-Kuhn-Tucker Optimality Criteria is

$$\frac{\partial F}{\partial y} = \frac{\partial S}{\partial y} + \mu_1 = 0$$

In this case, note that the Nash solution of this game is:

$$x^* \begin{cases} 1 \quad if \;\; y^* < Y \\ X \quad if \;\; y^* = Y \\ 0 \quad if \;\; y^* > Y \\ X = \dfrac{(C(p_E, E) + \Omega_E p_E) - (C(p_e, e) + \Omega_e p_e)}{F(\alpha_{PA}(E)) - F(1 - \beta_{PA}(e))} \end{cases}$$

$$y^* \begin{cases} 1 \quad if \;\; x^* < X \\ Y \quad if \;\; x^* = X \\ 0 \quad if \;\; x^* > X \\ Y = \dfrac{F(1 - \beta_{PA}(e)) - C_p}{F(1 - \beta_{PA}(e)) - F(\alpha_{PA}(E))} \end{cases}$$

This means that if $y^* < Y$, the port authority will inspect this ship. If $y^* > Y$ the port authority will not inspect the ship. Only when $y^* = Y$, will the port authority select a mixed strategy.

Similarly, if$x^* > X$, the best choice of the shipowner will be that doing some high intensity prevention. If $x^* < X$, the shipowner will spend a low effort on the ship. Only when $x^* = X$, will the shipowner select a mixed strategy.

7.1.5 Equilibrium between the port authority and the shipowner

A Nash equilibrium point is a pair of strategies that do not motivate any one of the players to change his strategy as long as the other stays with his strategy. So in this game $(X, Y)$is the only Nash equilibrium. This means that in equilibrium the port authority selects to inspect a ship with a probability X and not to inspect one with a probability $(1 - X)$. The shipowener selects high intensity prevention with a probability Y, and selects low intensity prevention with a probability $(1 - Y)$.

A chart can be used to express the Nash equilibrium. When the players select the mixed strategy, they select any pure strategy with a probability between $(0, 1)$. The reaction correspondence can be used to express the best choice when one player reacts to the other players mixed strategy. Reaction correspondences, also known as best response correspondences, are used in the proof of the existence of mixed strategy Nash equilibrium. Reaction correspondences are not "reaction functions" since functions must only have one value per argument, and many reaction correspondences will be undefined, namely a vertical line, for some opponent strategy choice.

In this game the port authority and the shipowner's reaction correspondence is:

The port authority:

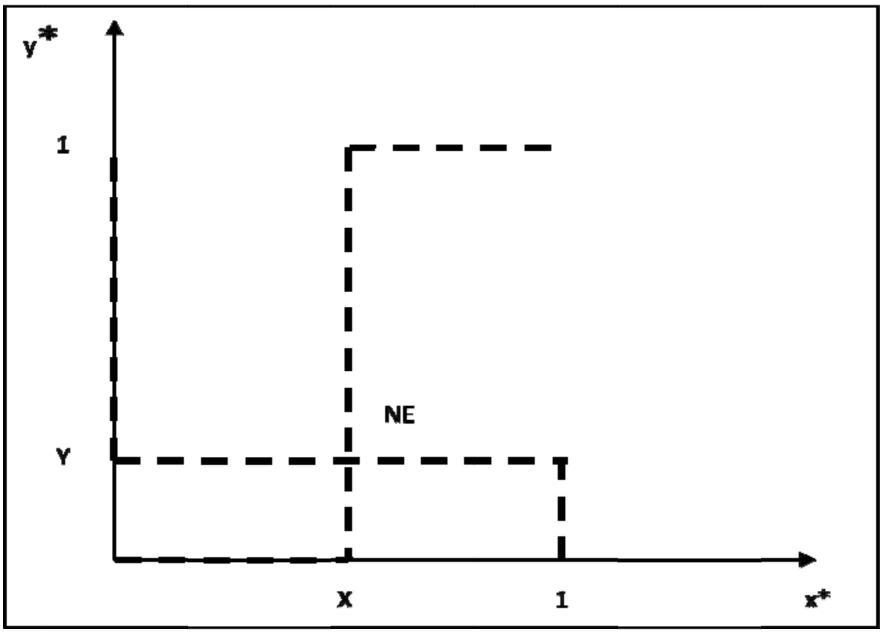
$$x^* = \begin{cases} 1 & if \ \ y^* < Y \\ [0,1] & if \ \ y^* = Y \\ 1 & if \ \ y^* > Y \end{cases}$$

The shipowner:

$$y^* = \begin{cases} 1 & if \ \ x^* < X \\ [0,1] & if \ \ x^* = X \\ 1 & if \ \ x^* > X \end{cases}$$

Response correspondences for all 2x2 normal form games can be drawn with a line for each player in a unit square strategy space. Figures 7-2 graphs the best response correspondences for this game. The dotted line in Figure 7-2 shows the optimal probability that the port authority plays "inspection" (in the x-axis), as a function of the probability that the shipowner plays "prevention" (shown in the y-axis). The interaction of the two curves is the Nash equilibrium.

Figure 7-2: Reaction correspondence



7.1.6 Determination of the NE

The Nash equilibrium of this mixed strategy is

$$X = \frac{(C(p_E, E) + \Omega_E p_E) - (C(p_e, e) + \Omega_e p_e)}{F\big(\alpha_{PA}(E)\big) - F\big(1 - \beta_{PA}(e)\big)}$$

$$= \frac{(C(p_e, e) + \Omega_e p_e) - (C(p_E, E) + \Omega_E p_E)}{F\big(1 - \alpha_{PA}(E) - \beta_{PA}(e)\big)}$$

$$Y = \frac{F\big(1 - \beta_{PA}(e)\big) - C_p}{F\big(1 - \beta_{PA}(e)\big) - F\big(\alpha_{PA}(E)\big)}$$

This means that the port authority will inspect a ship with a probability of X , and the shipowner will use high intensity prevention with a probability of Y . This equilibrium can also be explained as if there are lots of ships visiting port. The optimal inspection rate equa1 to X.

Among all these ships visiting port, Y percent of them will use high intensity prevention.

The Nash equilibrium is associated with the fine F, the cost of control of a vessel to the port authority C_p and the two types of errors α, β.

7.1.7 Effects of the penalty

Although, in practice the main punishment to the violating shipowners is detention, not a punitive penalty, in this study, the fine was assumed to exist, and the effect of the fine was analyzed with regard to the strategy.

Generally, the relationship between them is that when the value of F is not great enough to force the shipowner to improve his safety level, the port state authority needs to improve the port inspection rate after taking account of its social loss. When the value of F is great enough, its port authority can decrease the port inspection rate and the shipowner will still improve his safety level.

From the best optimal inspection rate X, if the fine is higher then the optimal inspection rate will be lower.

When the penalty cost F increases, the shipowner's expected loss may increase. In this circumstance his optimal effort level will increase in order to decrease the pressure from the increase in$F$.

$$Y = \frac{F\big(1-\beta_{PA}(e)\big)-C_p}{F\big(1-\beta_{PA}(e)\big)-F\big(\alpha_{PA}(E)\big)} = \frac{\big(1-\beta_{PA}(e)\big)-\frac{C_p}{F}}{F\big(1-\beta_{PA}(e)-\alpha_{PA}(E)\big)}$$

So

$$\frac{\partial Y}{\partial F} = \frac{C_p}{1-\beta_{PA}(e)-\alpha_{PA}(E)}\frac{1}{F^2}$$

This means that if the fine is higher then the shipowner will either take more care of his ship or will use less substandard ships.

7.2 Application of marine risk assessment in PSC

To characterize the optimal enforcement strategy, numerical techniques were used to highlight the optimal inspection strategy.

The analysis of the relationships between the variation of each cost parameter and the optimal inspection rate, and the variation of each cost parameter and the optimal effort level can help the port state authority to adjust its choice of the port inspection rate through changing each cost parameter.

7.1.1 Shipowner's effort

Shipowners play an important role in avoiding shipping accidents. It is widely recognized the human error plays a major role in most shipping accidents. The statistics made by the Transportation Safety Board of Canada (TSBC) showed that 74% of the accidents at sea attributes to human errors and 20% to technical failures. Human errors may include a lack of adequate knowledge and experience, technical inability, fatigue and lack of alertness, overworking and tiredness, etc. Among the human errors, the misjudgments of ship master and lack of communication among crew members were accessed as predominant causes (TSBC, 1998).

Besides the ship masters and crew, shipowners' responsibilities need to be analyzed in accident investigation. Firstly, shipowners decide the selection of masters and crew. Selecting experienced or non-experienced masters and crew will have some effect on the probability of accidents. Secondly, shipowners make the decision whether or not to train those crews. Appropriate training can make the crew equipped with adequate knowledge and experience and enhance mutual understanding of the crew. More importantly, crew intensity is decided by the shipowners. Fatigue is a significant causal factor in marine casualties (US Coast Guard Research and Development Center, 1996). The US Coast Guard analyzed 297 marine casualties and showed that fatigue was a contributing factor in 16% of critical vessel casualties and 33% of personnel injuries. One of the most extensive surveys made by the International Transport worker' Federation (ITF) showed that many seafarers were unaware of the legal safeguards that have been introduced and many shipowners were unwilling or unable to comply with the regulations.

Shipowners are also in charge of the installation and maintenance of shipping safety facilities. Although showing a crucial role in avoiding ship accidents, shipowners and their responsibilities have not been fully addressed in the present literature of maritime accident investigation. The aim of this paper is to integrate shipowners' efforts into ship accident analysis.

In section 6.2, the residual π_i were use to measure the ships safety condition. A positive π_i means that the accident happened, but that the estimated probability of casualty was less than 1, which means that this accident could have been avoided. This type of ship was defined as a substandard ship. We also define this shipowner made a substandard effort. Whereas a negative π_i means that the estimated probability of casualty is larger than 0, but the ship does not have an accident. This type of ship was defined as a standard ship. Then we define this shipowner made a standard effort, which decreases the probability of an accident.

7.1.2 The parameter estimation

Firstly, the probability of an accident occurring $p_j, j = E, e$ can be obtained from the result of risk assessment (section5.1). The estimated probability ($p_j, j = E, e$) of a ship having an accident is parameterized as an exponential function of shipping's operating characteristics.

The maintenance cost data was gathered from Drewry's publication "Ship Operating Cost Annual Review and Forecast'. The dataset includes the repair and maintenances costs for different vessel types of various sizes for the time period 2001-2010. Table6-5 lists the estimated repair and maintenances costs under different conditions.

The value of second hand ships were used as the loss once the accident happened. The loss of a different ship in a different situation may be different, so here this is only given as an example to show how this methodology works.

Here assume that the penalty function is a liner relationship with the expected loss of the accident. So the penalty function is

$$F = \omega \Omega_e p_e$$

7.1.3 Optimal inspection policy base on the marine risk assessment

The following sections present the results of the analysis. This analysis serves two purposes: (1) It is to obtain the optimal inspection rate for different vessel types; (2) it shows the effects of changing parameters on the optimal inspection rate.

Firstly, different types of vessels have different accident probabilities and expected losses when an accident occurs. So the inspection rate should be different. Putting this empirical data into the Nash equilibrium, the optimal inspection rate can be obtained. Here assume $\omega = 10,\ \alpha = \beta = 0$ and that the work of the authorities is perfect.

Table 7-3: The optimal inspection rate for different vessels

Vessel size	Smaller			Larger		
Vessel age	New	Average	Old	New	Average	Old
Bulk	0.053	0.076	0.056	0.052	0.062	0.056
Tanker	0.001	0.020	0.005	0.051	0.049	0.056
Container	0.002	0.023	0.047	0.042	0.058	0.050
Gen. cargo	0.021	0.011	0.002	0.046	0.025	0.027

Several patterns can be observed in Table 7-3. Firstly, the inspection rate for smaller new tankers is lowest, being about 0.1%, but with the increase in tanker size and age the rate is increasing very quickly, the optimal inspection rate for the tanker increasing to about 5.6%.

Secondly, bulk's inspection rate should be higher than the others, especially the LA bulk, where the rate should be larger than 7.5%, which is the highest.

Thirdly, bulk and general cargo ships have a more steady inspection rate. The rates for bulk should be kept at approximately 6%. Most types of general cargo should be inspected at approximately 0.2%.

Fourthly, larger size vessels should be inspected more often, especially tankers and container ships. That is because the expected loss of larger vessels is higher.

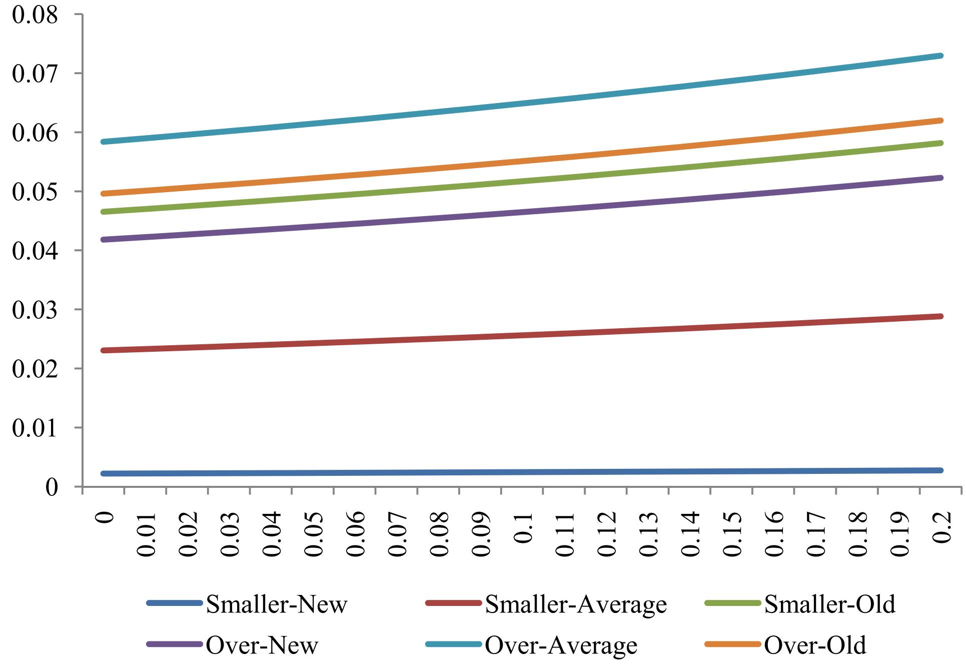
Fifthly, the rate for midterm age vessels is higher than both newer and older vessels, this being due to their having the highest accident probability.

Figure 7-3 shows the results of all possible inspection rates when α and β changes, and here we use the container ship as an example. The chart shows that with an increase in the two types of errors, the optimal inspection rate will increase too, especially for larger and median age container ships. The optimal inspection rate for newer and smaller size container ships does not show a significant increase following an increase of α and β.

So in practice, with a decrease in α andβ, which means that the authorities improve their accuracy, the authorities' workloads will decrease too, without increasing the loss of social welfare. For example, the optimal inspection rate for the larger average size and average age containership is about 5.8% if the work of the authorities is perfect, but if the two type error increases to 10%, then the optimal inspection rate increases to 7.3%.

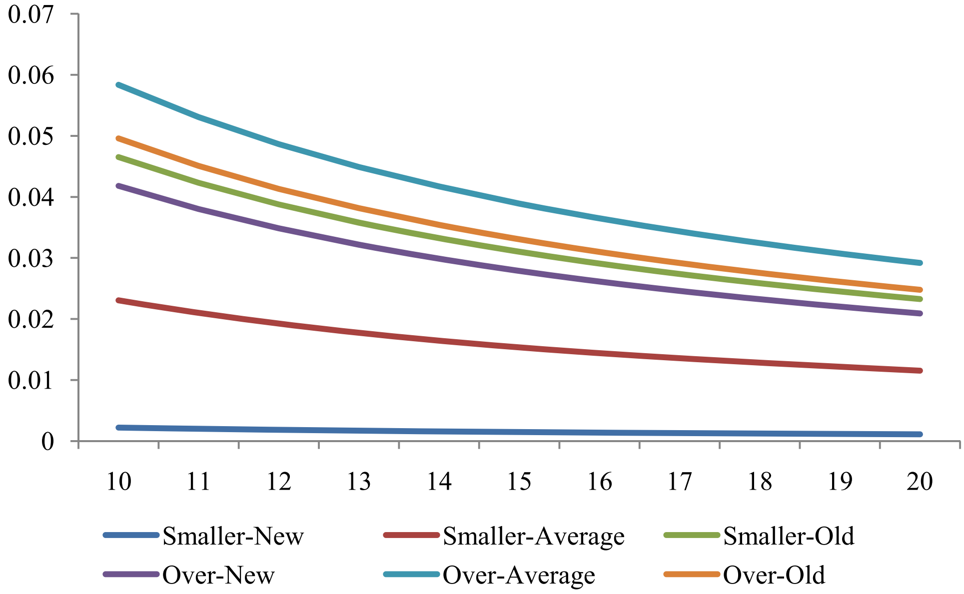
Another benefit of the authorities improving their accuracy is that shipowners' appeals will also decrease. Then the frequency of re-inspections will be lower, and the cost to both society and the shipowner will be saved.

Figure 7-3: Optimal inspection rates when α and β changes



Next, change the penalty parameters to examine the effects on the optimal inspection rate. Figure 7-4 shows the optimal inspecton rate when ω changes. Here, it is still assumed the work of the authorities is perfect $\alpha = \beta = 0$.

Figure 7-4: Optimal inspection rate when ω changes



With an increase in penalty, the optimal inspection rates show a significant decrease. For a penalty of $\omega = 10$, the optimal inspection rate for a larger and average age containership is $X = 5.8\%$. When $\omega = 20$, which means the penalty is doubled, the optimal rate is $X = 2.8\%$. The rate for newer and small size containerships does not show a significant decrease. So when the value of F is great enough, the port authority can decrease the port inspection rate.

In this section, we firstly develop a model to decide on the optimal inspection policy with an aim to save costs on inspection whilst keeping deterrence pressure on potential wrongdoers. A bi-matrix game is built between the authorities and the ship operators, in which two types of errors are considered. Then we used numerical techniques to show the optimal inspection strategy, which give an intuitionist of the optimal enforcement strategy. Used the result of risk assessment, we get the optimal inspection rate about different type vessel and the effects of changing parameters on the optimal inspection rate.

In conclusion, the optimal inspection rate obtained from the model can yield significant savings, as well as prevent potential violations by ship operators.

Chapter 8：Conclusions

In this chapter the conclusions of the research are presented. These conclusions describe how this research met the initial aims and objectives that were originally stated in section 1.4.

- Probability of accident

Risk is defined as a combination of the probability of occurrence of a marine accident and the degree of its possible consequences. Reducing the probability is a feasible method of reducing the risk level, and this research contributes to predicting the probability of an accident in the risk assessment program.

Traditionally, the simplest way to estimate the probability of marine accidents has been to contemplate accident statistics or expert estimations. However, both of these methods have certain limitations.

This research, based on the safety performance of global vessels, found various risk indicators that can be used to indicate the probability of an accident. Then multivariate logistic regression was used to measure the probability of the occurrence of an accident through historical data on safety indicators, such as vessel age, type, registration and classification.

The result reveals that vessel age is associated with a decrease in the probability, and that the probability increases as the vessel size increases. The general cargo group of vessels is the type most at risk, and the second group most at risk is passenger vessels. The tankers group has the smallest probability of accident. Compared with non-IACS members, vessels classified by IACS members have a lower probability of accident, and vessels registered in a flag-of-convenience country have a higher probability.

- Comprehensive database

Secondly, a comprehensive database was built for this analysis. The shipping dataset is a combination of four individual datasets, which when aggregated together accounts for approximately 140,000 ships. This dataset includes an approximation of the total ships whatever in existence and the total lost.

This database not only includes static data, but also dynamic data. The static data comes mainly from PC registers (Lloyd's Register, London), which is a powerful database describing each vessel, with over 200 variables such as vessel flag, date of building, vessel tonnage etc.

The inspection database consists of 319,623 inspection reports from three main Memoranda of Understanding (MoU) for the time period January 2000 to 2008.

The casualty dataset consists of 7,966 records for the time period 1993-2008, and is a combination of data received from World Casualty Statistics and the International Maritime Organization (IMO).

- Quantitative risk assessment using BN

This part presented an innovative approach toward integrating logistic regression and Bayesian Networking together into risk assessment. The approach was developed and applied to a case study in the maritime industry, but it can apply to other industries as well. The BN model provided the probability that a particular combination of values of the factors occurred in the system, and assessed how the various factors simultaneously affected a vessel's safety level. Although the maintenance cost for keeping a standard ship is higher, the expected overall cost is lower than that of a substandard ship.

- Case study

Fourthly, a case study applying this risk assessment program in the port state control program was presented. In this part, a model was first developed to decide on the optimal inspection policy, with the aim of saving on inspection costs whilst at the same time keeping deterrence pressure on potential wrongdoers. A bi-matrix game was built between the authorities and the ship operators, in which two types of errors are taken into account.

To characterize the optimal enforcement strategy, numerical techniques were used to show the optimal inspection strategy. The optimal inspection rate for different vessel types, and the effects of changing parameters on the optimal inspection rate, was examined in the light of the risk assessment results.

- Future work

The concept of the marine safety index is the prime result. With the development of a dynamic shipping database even more variables can be added, such as real-time result monitoring, to improve and perfect that safety index.

This research mainly focuses on the estimation of probability in risk assessment. Another important component, the consequences of marine accidents, should be evaluated using appropriate methods in future work.

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APPENDIX:

Table A-1: The selection of vessel types

Level 1	Level 2	Level 3
Dry Cargo	General Cargo	General Cargo Ship
		General Cargo Barge, Propelled
		Deck Cargo Ship
		Palletised Cargo Ship
	Ro-Ro Cargo	Ro-Ro Cargo Ship
		Vehicles Carrier
		Landing Craft
	Other Dry Cargo	Refrigerated Cargo
		Heavy Load Carrier
		Livestock Carrier
Tanker	Liquefied Gas	LNG Tanker
		LPG Tanker
		CO2 Tanker
	Chemical	Chemical Tanker
		Wine Tanker
		Vegetable Oil Tanker
		Latex Tanker
	Oil	Crude Oil Tanker
		Oil Productes Tanker
		Bitumen Tanker
		Coal/Oil Mixture Tanker
	Other Liquids	Water Tanker
		Alcohol Tanker

Table A-1: The selection of vessel types (Continue)

Level 1	Level 2	Level 3
Bulker	Bulk Dry	Bulk Carrier
		Ore Carrier
	Bulk Dry/Oil	Bulk/Oil Carrier
		Ore/Oil Carrier
	Self Discharging Bulk Dry	Self Discharging Bulk Dry
Container	Container Ship(Fully Cellular)	
	Container Ship(Fully Cellular with Ro-Ro Facility)	
	Container Barge, propelled	
Passenger	Passenger	Passenger(Cruise) Ship
		Passenger Ship
	Passenger/Ro-Ro Cargo	Passenger/Ro-Ro Cargo
		Passenger/Landing Craft
	Passenger/General Cargo	Passenger/General Cargo
Other	Fishing	Fish Catching
		Other Fishing
	Offshore	Offshore Supply
		Other Offshore
	Miscellaneous	Towing/Pushing
		Dredging
		Other Activities

Table A-2: Summary of main variables and their significance: Vessel Flag

Variable	Country	Coefficient	P-value	Marginal Probability
x40	Panama	1.01	0.000	0.040
x41	United States	1.37	0.000	0.055
x42	Japan	-0.85	0.000	-0.034
x43	Unknown	-1.55	0.000	-0.062
x44	Indonesia	0.57	0.001	0.023
x45	China	-0.3	0.034	-0.012
x46	Russia	2.37	0.000	0.094
x47	Singapore	0.38	0.010	0.015
x48	Liberia	0.62	0.000	0.025
x49	Korea (South)	0.63	0.000	0.025
x50	United Kingdom	0.77	0.000	0.031
x51	Norway	0.97	0.000	0.039
x52	Netherlands	-0.73	0.000	-0.029
x53	Philippines	0.39	0.014	0.015
x54	Malta	0.99	0.000	0.039
x55	Greece	0.78	0.000	0.031
x56	Marshall Islands	-0.22	0.195	-0.009
x57	Italy	0.88	0.000	0.035
x58	Hong Kong	0.08	0.625	0.003
x59	Bahamas	0.71	0.000	0.028
x60	Spain	1.24	0.000	0.049
x61	Turkey	0.99	0.000	0.040
x62	India	-0.45	0.036	-0.018
x63	Germany	0.67	0.000	0.027
x64	Antigua And Barbuda	0.79	0.000	0.032
x65	Cyprus	0.81	0.000	0.032
x66	Malaysia	0.39	0.048	0.016
x67	Viet Nam	0.55	0.016	0.022
x68	Honduras	1.33	0.000	0.053
x69	St Vincent	-0.09	0.616	-0.004
x70	Canada	1.12	0.000	0.045
x71	Cambodia	0.87	0.000	0.035
x72	Thailand	0.6	0.002	0.024
x73	Mexico	-3.75	0.000	-0.149
x74	France	0.10	0.564	0.004
x75	Peru	0.68	0.061	0.027

Table A-2: Summary of main variables and their significance: Vessel Flag (Continue)

Variable	Country	Coefficient	P-value	Marginal Probability
x76	Brazil	-2.89	0.000	-0.115
x77	Australia	-2.89	0.000	-0.115
x78	Cayman Islands	-1.16	0.002	-0.046
x79	Ukraine	0.21	0.397	0.008
x80	Argentina	1.18	0.000	0.047
x81	Taiwan, China	-0.04	0.893	-0.002
x82	United Arab Emirates	-0.12	0.735	-0.005
x83	Chile	1.73	0.000	0.069
x84	Sweden	-0.18	0.464	-0.007
x85	Iran	-3.26	0.000	-0.130
x86	Danish	0.89	0.000	0.036
x87	Vanuatu	0.10	0.746	0.004
x88	Belize	1.88	0.000	0.075
x89	Morocco	-0.30	0.377	-0.012
x90	Nigeria	0.21	0.391	0.008
x91	Isle of Man	-0.36	0.140	-0.014
x92	Egypt	0.49	0.119	0.020
x93	Venezuela	0.20	0.464	0.008
x94	Denmark	1.09	0.000	0.043
x95	Belgium	-0.81	0.004	-0.032
x96	Portugal	0.28	0.276	0.011
x97	Poland	0.62	0.102	0.025
x98	Saudi Arabia	0.00	0.993	0.000
x99	Sierra Leone	0.28	0.266	0.011
x100	Gibraltar	0.47	0.065	0.019
x101	Bangladesh	-0.98	0.006	-0.039
x102	Croatia	1.56	0.000	0.062
x103	Azerbaijan	1.80	0.001	0.072
x104	Finland	0.23	0.398	0.009
x105	Comoros	0.21	0.423	0.009
x106	Georgia	1.25	0.000	0.050
x107	Ecuador	1.35	0.001	0.054
x108	Korea (North)	0.78	0.001	0.031
x109	South Africa	-1.33	0.001	-0.053
x110	St Kitts & Nevis	0.55	0.037	0.022
x111	Iceland	1.61	0.000	0.064
x112	Ireland	-0.72	0.020	-0.029
x113	Ghana	-0.27	0.498	-0.011
x114	Kuwait	-1.97	0.000	-0.079

Table A-2: Summary of main variables and their significance: Vessel Flag (Continue)

Variable	Country	Coefficient	P-value	Marginal Probability
x115	Bahrain	-1.36	0.040	-0.054
x116	Bermuda	0.11	0.715	0.004
x117	Colombia	0.63	0.250	0.025
x118	Romania	0.70	0.043	0.028
x119	Tuvalu	0.22	0.548	0.009
x120	Senegal	-0.19	0.720	-0.007
x121	USSR	-4.87	0.329	-0.194
x122	France (FIS)	-1.60	0.002	-0.064
x123	Luxembourg	-1.11	0.069	-0.044
x124	New Zealand	-2.33	0.000	-0.093
x125	Namibia	0.74	0.022	0.030
x126	Libya	0.08	0.907	0.003
x127	Mauritania	0.80	0.018	0.032
x128	Mongolia	0.60	0.093	0.024
x129	Latvia	1.02	0.001	0.041
x130	Faeroes	1.17	0.018	0.047
x131	Saint Vincent	12.69	0.182	0.506
x132	Madeira (MAR)	1.05	0.003	0.042
x133	Angola	-0.95	0.163	-0.038
x134	Barbados	0.87	0.012	0.035
x135	Guyana	-0.15	0.730	-0.006
x136	Uruguay	-1.14	0.003	-0.045
x137	Bulgaria	1.18	0.008	0.047
x138	Algeria	-0.26	0.668	-0.010
x139	Mozambique	-0.64	0.145	-0.026
x140	Papua New Guinea	-0.07	0.908	-0.003
x141	Qatar	-0.09	0.887	-0.003
x142	Dominica	1.73	0.000	0.069
x143	Lithuania	1.11	0.000	0.044
x144	Trinidad Tobago	0.12	0.804	0.005
x145	Estonia	0.95	0.01	0.038
x146	Myanmar	-5.93	0.315	-0.236
x147	Cook Islands	0.19	0.591	0.008
x148	Sri Lanka	0.43	0.258	0.017
x149	Syria	2.03	0.000	0.081
x150	Madagascar	-1.54	0.012	-0.061
x151	Kazakhstan	-1.33	0.165	-0.053
x152	Maldives	-2.4	0.000	-0.096
x153	Lebanon	0.89	0.018	0.035

Table A-3: The conditional probability of an accident under different conditions: Dry cargo

Dry cargo												
Ship safety condition	Std											
Vessel size	Smaller											
Vessel age	Young				Average				Old			
Flag state	Closed		Open		Closed		Open		Closed		Open	
Classification society	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS
Accident	0.12	0.04	0.17	0.09	0.09	0.03	0.10	0.07	0.06	0.02	0.08	0.05
Non-accident	0.88	0.96	0.83	0.91	0.91	0.97	0.90	0.93	0.94	0.98	0.92	0.95
Ship safety condition	Std											
Vessel size	Larger											
Vessel age	Young				Average				Old			
Flag state	Closed		Open		Closed		Open		Closed		Open	
Classification society	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS
Accident	0.18	0.08	0.25	0.14	0.12	0.05	0.18	0.09	0.09	0.03	0.13	0.06
Non-accident	0.82	0.92	0.75	0.86	0.88	0.95	0.82	0.91	0.91	0.97	0.87	0.94
Ship safety condition	Substd											
Vessel size	Smaller											
Vessel age	Young				Average				Old			
Flag state	Closed		Open		Closed		Open		Closed		Open	
Classification society	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS
Accident	0.11	0.18	0.16	0.15	0.17	0.07	0.25	0.17	0.14	0.12	0.18	0.05
Non-accident	0.89	0.82	0.84	0.85	0.83	0.93	0.75	0.83	0.86	0.88	0.82	0.95
Ship safety condition	Substd											
Vessel size	Larger											
Vessel age	Young				Average				Old			
Flag state	Closed		Open		Closed		Open		Closed		Open	
Classification society	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS
Accident	0.36	0.18	0.41	0.24	0.21	0.16	0.32	0.15	0.21	0.11	0.25	0.14
Non-accident	0.64	0.82	0.59	0.76	0.79	0.84	0.68	0.85	0.79	0.89	0.75	0.86

Table A-4: The conditional probability of an accident under different conditions: Tanker

Tanker												
Ship safety condition	Std											
Vessel size	Smaller											
Vessel age	Young				Average				Old			
Flag state	Closed		Open		Closed		Open		Closed		Open	
Classification society	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS
Accident	0.06	0.02	0.13	0.03	0.04	0.01	0.05	0.02	0.03	0.01	0.03	0.01
Non-accident	0.94	0.98	0.87	0.97	0.96	0.99	0.95	0.98	0.97	0.99	0.97	0.99
Ship safety condition	Std											
Vessel size	Larger											
Vessel age	Young				Average				Old			
Flag state	Closed		Open		Closed		Open		Closed		Open	
Classification society	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS
Accident	0.16	0.05	0.17	0.06	0.08	0.04	0.16	0.05	0.06	0.03	0.09	0.03
Non-accident	0.84	0.95	0.83	0.94	0.92	0.96	0.84	0.95	0.94	0.97	0.91	0.97
Ship safety condition	Substd											
Vessel size	Smaller											
Vessel age	Young				Average				Old			
Flag state	Closed		Open		Closed		Open		Closed		Open	
Classification society	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS
Accident	0.08	0.03	0.08	0.07	0.11	0.12	0.16	0.07	0.09	0.05	0.09	0.03
Non-accident	0.92	0.97	0.92	0.93	0.89	0.88	0.84	0.93	0.91	0.95	0.91	0.97
Ship safety condition	Substd											
Vessel size	Larger											
Vessel age	Young				Average				Old			
Flag state	Closed		Open		Closed		Open		Closed		Open	
Classification society	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS
Accident	0.24	0.14	0.36	0.16	0.16	0.16	0.22	0.18	0.27	0.21	0.21	0.09
Non-accident	0.76	0.86	0.64	0.84	0.84	0.84	0.78	0.82	0.73	0.79	0.79	0.91

Table A-5: The conditional probability of an accident under different conditions: Passenger

Passenger												
Ship safety condition	Std											
Vessel size	Smaller											
Vessel age	Young				Average				Old			
Flag state	Closed		Open		Closed		Open		Closed		Open	
Classification society	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS
Accident	0.09	0.04	0.12	0.04	0.07	0.02	0.07	0.01	0.05	0.01	0.05	0.01
Non-accident	0.91	0.96	0.88	0.96	0.93	0.98	0.93	0.99	0.95	0.99	0.95	0.99
Ship safety condition	Std											
Vessel size	Larger											
Vessel age	Young				Average				Old			
Flag state	Closed		Open		Closed		Open		Closed		Open	
Classification society	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS
Accident	0.13	0.08	0.24	0.12	0.11	0.05	0.16	0.06	0.07	0.03	0.08	0.04
Non-accident	0.87	0.92	0.76	0.88	0.89	0.95	0.84	0.94	0.93	0.97	0.92	0.96
Ship safety condition	Substd											
Vessel size	Smaller											
Vessel age	Young				Average				Old			
Flag state	Closed		Open		Closed		Open		Closed		Open	
Classification society	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS
Accident	0.15	0.03	0.08	0.05	0.19	0.04	0.18	0.10	0.08	0.02	0.05	0.02
Non-accident	0.85	0.97	0.92	0.95	0.81	0.96	0.82	0.90	0.92	0.98	0.95	0.98
Ship safety condition	Substd											
Vessel size	Larger											
Vessel age	Young				Average				Old			
Flag state	Closed		Open		Closed		Open		Closed		Open	
Classification society	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS
Accident	0.27	0.18	0.31	0.19	0.22	0.23	0.16	0.17	0.13	0.06	0.20	0.10
Non-accident	0.73	0.82	0.69	0.81	0.78	0.77	0.84	0.83	0.87	0.94	0.80	0.90

Table A-6: The conditional probability of an accident under different conditions: Bulker

Bulker												
Ship safety condition	Std											
Vessel size	Smaller											
Vessel age	Young				Average				Old			
Flag state	Closed		Open		Closed		Open		Closed		Open	
Classification society	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS
Accident	0.10	0.04	0.14	0.06	0.05	0.02	0.08	0.04	0.04	0.02	0.06	0.03
Non-accident	0.90	0.96	0.86	0.94	0.95	0.98	0.92	0.96	0.96	0.98	0.94	0.97
Ship safety condition	Std											
Vessel size	Larger											
Vessel age	Young				Average				Old			
Flag state	Closed		Open		Closed		Open		Closed		Open	
Classification society	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS
Accident	0.19	0.05	0.26	0.07	0.09	0.03	0.14	0.05	0.08	0.02	0.08	0.04
Non-accident	0.81	0.95	0.74	0.93	0.91	0.97	0.86	0.95	0.92	0.98	0.92	0.96
Ship safety condition	Substd											
Vessel size	Smaller											
Vessel age	Young				Average				Old			
Flag state	Closed		Open		Closed		Open		Closed		Open	
Classification society	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS
Accident	0.13	0.05	0.24	0.20	0.19	0.21	0.28	0.23	0.14	0.11	0.22	0.13
Non-accident	0.87	0.95	0.76	0.80	0.81	0.79	0.72	0.77	0.86	0.89	0.78	0.87
Ship safety condition	Substd											
Vessel size	Larger											
Vessel age	Young				Average				Old			
Flag state	Closed		Open		Closed		Open		Closed		Open	
Classification society	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS	Non IACS	IACS
Accident	0.39	0.18	0.39	0.17	0.32	0.13	0.32	0.17	0.26	0.12	0.30	0.12
Non-accident	0.61	0.82	0.61	0.83	0.68	0.87	0.68	0.83	0.74	0.88	0.70	0.88