RISK-BASED GAME MODELLING FOR PORT STATE CONTROL INSPECTIONS

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Abstract

This thesis aims to develop a new way for port authorities to predict, analyse and make decisions in Port State Control (PSC) inspections. Under the New Inspection Regime (NIR), it is necessary to not only figure out the influence of new regime to the PSC system, but also provide some technical tools capable of predicting the inspection results and supporting the decision-making of port authorities when regulating the inspection policy.

The study consists of analysis from multiple perspectives, both qualitative and quantitative. The risk factors influencing the inspection results and the decision-making of port authorities under NIR are identified through the practical inspection records and related literature. The Paris Memorandum of Understanding (MoU) offers the historical inspection records within the region of Europe and the North Atlantic basin, reflecting different conditions in different periods. Given the different inspection system since 2011, port authorities require a brand new perception of the new inspection regime to estimate the inspection results, and further make decisions when making their own inspection policy.

To achieve the objective, an incorporation of two types of models that have proved popular and superior is applied in this study. One is the risk assessment model of Bayesian network (BN), the other is the decision-making model of game theory.

The BN models in this research utilize a data-driven approach called Tree Augmented Naïve (TAN) learning to derive the structure of the models. Based on the inspection reports collected from Paris MoU, two BNs that represent the situations of Paris MoU inspection system in different periods are constructed. Company performance, the new indicator, is viewed as one of the important factors influencing the inspection results for the first time and considered in the models. The BN model after the implementation of NIR can serve as the prediction tool for estimating inspection results under dynamic situations. Additionally, a comparative analysis between two models is conducted to clarify the influence on PSC inspection system brought by NIR.

When constructing the non-cooperative strategic game model between port authorities and ship owners under NIR, the BN model outcomes play a crucial role in this process, highlighting the novelty of this model. Through the analysis and calculation on the payoff matrix, a Nash equilibrium solution representing the theoretical optimal inspection rate for port authorities is obtained.

To validate the feasibility and practical significance of the game model, an empirical study is conducted. The statistics are quantitative and collected from different sources, i.e. Basic vessel information from the World Shipping Encyclopaedia (WSE), casualty information from IMO and Lloyd's Register of Shipping, PSC Inspection records from Paris MoU online inspection database, and the estimated value of different cost types from Drewry Shipping Consultants Ltd. The empirical study illustrates the insights of the optimal inspection policy for port authorities (i.e. with the increase of punishment severity, the optimal inspection rates experience a decreasing trend whatever the vessel condition), as well as providing suggestions for them when formulating the optimal inspection policy under various situations.

Based on the BN model and the strategic game model after the implementation of NIR, the thesis eventually proposes a decision-making framework for port authorities to prioritise and select the strategies under different situations. The six-step framework incorporates a risk assessment approach and decision-making approach to provide a novel way to rank the candidate options of port authorities in terms of their resources, which enables decision-makers to find optimal strategies to improve the performance of the PSC inspection system under dynamic business environments.

In general, this thesis provides important insights for port authorities to ensure that optimal inspection actions are taken to improve safety at sea in a cost effective manner. The two technical tools (i.e. the dynamic prediction tool for inspection results & the optimal inspection strategy), and the decision-making framework proposed in this project are helpful for port authorities within the Paris MoU region when regulating their inspection policy under NIR. Meanwhile, the comparative analysis in this study further clarifies the influence of NIR on new inspection system from different angles for the first time, demonstrating the introduction and implementation of NIR is a wise and positive decision.

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This thesis is dedicated to my family

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Abbreviations

ABN	Augmented Naïve Bayesian Network
ACO	Ant Colony Optimisation
ADR	Average Detention Rate
AIS	Artificial Immune System
BBN	Bayesian Belief Network
BN	Bayesian Network
CB	Conditional independence and Bayesian learning
CI	Conditional Independence
CIC	Concentrated Inspection Campaign
CONAR	Construct and Repair
CPD	Conditional Probability Distribution
CPT	Conditional Probability Table
DWT	Dead Weight Tonnage
EDA	Estimation of Distribution Algorithms
EMSA	European Maritime Safety Agency
EU	European Union
FBN	Fuzzy Bayesian Network
FSA	Formal Safety Assessment
FTA	Fault Tree Analysis
GA	Genetic Algorithms
HRI	High Risk Inference
HRS	High Risk Ship
IAME	International Association of Maritime Economists
IEEE	Institute of Electrical and Electronics Engineers
ILO	International Labour organization
IMO	International Maritime Organization
ISM	International Shipping Management
ITS	Intelligent Transportation System
KPI	Key Performance Indicator
LISS	Logistics, Informatics and Service Sciences
LRI	Low Risk Inference

LRS	Low Risk Ship
MARPOL	International Convention for the Prevention of Pollution from Ships
MLC	Maritime Labour Convention
MLE	Maximum Likelihood Estimator
MoU	Memorandum of Understanding
MRRA	Model based on Relative Risk Assessment
NO.N	Naïve Bayesian Network
NIR	New Inspection Regime
PID	Percentage of Inspections with Deficiencies
PMI	Percentage of Mutual Information
PSC	Port State Control
PSCO	PSC Officer
PSO	Particle Swarm Optimization
REST	Restricted Structure
RO	Recognized organization
SOLAS	International Convention for the Safety of Life at Sea
SRP	Ship Risk Profile
SRS	Standard Risk Ship
STCW	International Convention on Standards of Training, Certification and Watchkeeping for Seafarers
SVM	Support Vector Machine
TAN	Tree Augmented Naïve
TRI	True Risk Influence
UNCTAD	United Nations Conference on Trade and Development
VLCC	Very Large Crude Carrier
WGB	White, Grey and Black
WSE	World Shipping Encyclopaedia
IACS	International Association of Classification Societies

CHAPTER 1 INTRODUCTION

This chapter describes the background of the research and explains the principal objectives that are developed through investigating and browsing related literature. The applied methods constitute the final models, as well as highlighting the research question in this thesis. Further, the contribution of the research is illustrated, demonstrating the role of the proposed models in real practice.

1.1 RESEARCH BACKGROUND

Over the last decades, Maritime transport has played an increasingly important role in the world's economy as over 90% of international trade is carried by sea and it is, by far, the most cost-effective way to move mass goods and raw materials around the world (Ducruet, et al., 2016). Take the maritime transport conditions in Europe for example; the coastline of the European Union is many thousands of kilometres in length and contains well over 1,000 individual ports. Every year, these ports handle 3.5 billion tons of goods and transport over 350 million passengers on thousands of ship journeys, accounting for around 90% of EU external trade and around 40% of trade between EU countries.

However, back to about 20 years ago, Perrow (1999) pointed out that 'Tankers carrying LNG have the potential to blow up a whole city', demonstrating the severity of maritime accidents from an academic perspective. The unprecedented growing rate of maritime transportation in recent years on the one hand contributes to industrial prosperity and individual benefits, but on the other hand renders threats and risks to the maritime industry, indicating it is a high-risk transportation mode having high potential to cause catastrophes (Hetherington, et al., 2006). A small mistake of the ship owner or a deficiency of the vessel quality may result in different types of severe maritime accidents, including but not limited to ship collisions, stranding, fire, and oil spill that could cause large property losses, environmental pollution and casualties. For instance, the grounding of the Exxon Valdez (Figure 1.1), the capsizing of the Herald of Free Enterprise (Figure 1.2) and the Estonia passenger ferry (Figure 1.3) are well-known major accidents in maritime transportation. These maritime accidents attracted the attention of the world on maritime safety (Li, et al., 2014; Yang, et al., 2013; Yang, et al., 2014).

Figure 1.1 The grounding of Exxon Valdez
(Source: The Atlantic)

Figure 1.2 The capsizing of the Herald of Free Enterprise
(Source: BBC NEWS)

Figure 1.3 The MS Estonia Ship disaster
(Source: Marine Insight)

Hence, it is of vital importance that maritime transport should be operated in a safe, secure and environmentally friendly way. Traditional flag state control has its limits in terms of ensuring the implementation of maritime safety regulations by ship owners, particularly those choosing open registration. In the past, the responsibility for ensuring vessels comply with the provisions of national and international rules rests upon the owners, masters and the flag states. Some flag states failed to fulfil their commitments contained in agreed international legal instruments, and subsequently, some vessels sailed in an unsafe condition, threatening the lives of the crew as well as the marine environment. Therefore, Port State Control (PSC), which was originally intended to be a backup to flag state implementation in 1982, is gradually becoming a system of harmonized inspection procedures designed to target sub-standard vessels with the main objective being their eventual elimination.

1.1.1 Port state control

Specifically, PSC is an internationally agreed regime for the inspection of foreign vessels in other national ports to verify that the condition of a vessel and its equipment complies with the requirements of international regulations. The relevant regulations include International Convention for the Safety of Life at Sea (SOLAS), International Convention for the Prevention of Pollution from Ships (MARPOL), International Convention on Standards of Training, Certification and Watch keeping for Seafarers (STCW), and Maritime Labour Convention (MLC). PSC renders port authorities the ability to inspect the vessels in their own ports to avoid illegal actions of ship owners and maritime accidents. The inspections involve checking whether the vessel is manned and operated in compliance with applicable international laws and regulations, and verifying the competency of the ship's master and officers (IMO). It is noteworthy that PSC inspections are restricted to merchant vessels and do not include fishing vessels and military craft. Meanwhile, every nation has the right to enact its own laws to impose requirements on foreign vessels trading in its waters based on its national conditions.

In order to provide a better environment for PSC inspection, the European Union (EU) has put in place specific maritime legislation: the port state control Directive 2009/16/EC as amended and its three implementing regulations (Commission Regulation No 428/2010, Commission Regulation No 801/2010 and Commission Regulation No 802/2010). This legislation aims at ensuring that there is effective control of compliance with international standards by vessels in EU ports and, thereby, ensuring that vessels sailing in EU waters have been appropriately constructed and are adequately maintained. Acting as the last safety line of defence against sub-standard vessels, PSC effectively restricts the appearance of the vessels not fully following the relevant safety regulations with the help of this legislation.

1.1.2 Memorandum of Understanding (MoU) on PSC

MoU on PSC is the administrative agreement between maritime authorities, which aims at increasing maritime safety, protecting the marine environment, and improving living and working conditions on board ships. It formulates the rules and regulations to ensure the effectiveness of PSC.

Back to 1978, an agreement called the 'Hague Memorandum’ signed by a number of maritime authorities in Western Europe was developed. It dealt mainly with enforcement of shipboard living and working conditions as required by International Labour Organization (ILO) Convention No. 147. However, when the memorandum was about to come into effect in March 1978, a massive oil spill occurred off the coast of Brittany (France) because of the grounding of the VLCC ‘Amoco Cadiz’. This maritime disaster caused a strong political and public outcry in Europe for more stringent regulations with regard to the safety of marine shipping. The pressure from public opinion resulted in a more comprehensive memorandum that covered:

1) Safety of life at sea

2) Prevention of pollution by ships

3) Living and working conditions on board ships

Subsequently a new ‘Memorandum of Understanding on Port State Control in Implementing Agreements on Maritime Safety and Protection of the marine Environment’ (MoU 1982) was approved in January on 1982 by fourteen European countries at a Ministerial Conference held in Paris. It then entered into operation on July 1st, 1982. The introduction of MoU 1982 marked the implementation of PSC.

Since that date, the Memorandum has been amended several times to accommodate new safety and marine environment requirements stemming from the International Maritime Organization (IMO) and requirements related to working and living conditions of seafarers. Several regional PSC organisations have been established over the decades, containing various regions including Europe and the north Atlantic (Paris MoU), Asia and the Pacific (Tokyo MoU), Latin America (Acuerdo de Viña del Mar), Caribbean (Caribbean MoU), West and Central Africa (Abuja MoU), the Black Sea region (Black Sea MoU), the Mediterranean (Mediterranean MoU), the Indian Ocean (Indian Ocean MoU) and the Riyadh MoU. The United States Coast Guard maintain the tenth PSC regime.

Among these regional organisations, the Paris MoU is the oldest and has the widest range of jurisdiction. It is set in order to eliminate the operation of sub-standard vessels through a harmonized system of PSC covering the waters of the European coastal States and the North Atlantic basin from North America to Europe. The current member states of the Paris MoU includes Belgium, Bulgaria, Canada, Croatia, Cyprus, Denmark, Estonia, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Latvia, Lithuania, Malta, the Netherlands, Norway, Poland, Portugal, Romania, the Russian Federation, Slovenia, Spain, Sweden and the United Kingdom.

Annually more than 18,000 inspections take place on board foreign vessels in the Paris MoU ports, ensuring that these vessels meet international safety, security and environmental standards, and that crewmembers have adequate living and working conditions. There is no doubt that the number of inspections executed within the Paris MoU region is the highest of any region.

In this study, the inspection records used for analysis are derived from the Paris MoU online inspection database (https://www.parismou.org/inspection-search).

1.1.3 New Inspection Regime (NIR)

The New Inspection Regime (NIR) was developed by a task force led by the EC and adopted by the Paris MoU at its committee meeting held in Reykjavik, Iceland (May 2009). It was also the core content of the Port State Control Directive 2009/16/EC, which had been published in the Official Journal on 28/05/2009.

With the introduction of the NIR, the 25% quota for inspections to be performed by each individual member state is abandoned. As an alternative, a 'fair share' scheme is developed. The fair share scheme takes account of individual ship calls in a member state versus the individual ship calls of all member states. The port call information must be provided by the member states through SafeSeaNet, and will then be transferred to the information system of PSC.

The targeting of vessels is based on a ‘Ship Risk Profile’ (SRP). The SRP Calculator can be used to evaluate if a ship is viewed as High Risk Ship (HRS), Standard Risk Ship (SRS) or Low Risk Ship (LRS). The company performance criteria for the calculation of the Ship Risk Profile is a new parameter in the Paris MoU. The Paris MoU has established a formula called ‘Company Performance’ that takes into account the historical events such as deficiencies, detentions and good inspections in the last 36 months of the International Shipping Management (ISM) Company’s fleet, and compares it to the average level of all vessels inspected within the Pars MoU regions to determine the performance level of this ISM company. ISM Companies are ranked as having a very low, low, medium or high performance.

The new database for PSC, named THETIS, replaces the former system ‘SIReNaC’ and is managed, hosted and operated by European Maritime Safety Agency (EMSA). The THETIS serves as a platform to guide the inspectors based on the complicated targeting procedures, and as a central archive for storing inspection results and presenting a comprehensive overview of all inspected vessels. Considering the latest inspection information, it automatically recalculates the SRP on a daily basis.

In general, the introduction of NIR improved the PSC system from the following aspects:

1) Risk-based targeting

2) Less flexibility for port authority in selecting vessels for inspection

3) Adjust national commitment to regional commitment

4) Further refusal of access provisions

5) Benchmarking of vessel flag, recognized organization (RO) and International shipping management (ISM) company

6) Widened scope from ports to ports and anchorages

7) The introduction of 'Company Performance' index

Since being implemented in 2011, NIR has transformed and modernized the PSC inspection system in the Paris MoU region. The main objective during the development of NIR has been to reward quality shipping and to intensify control and sanctions on vessels with poor performance. It introduces several radical changes compared with the old system, which was based on the agreement 30 years ago. These changes are necessary to bring the Paris MoU in line again with the global maritime developments, the introduction of new IMO instruments and a better-balanced method of targeting and inspection of vessels.

1.1.4 Summary

In the past decades, PSC, the last safety line of defence against sub-standard vessels, has contributed a lot in preventing the illegal actions of ship owners and ensuring maritime safety. It is however well noted that although risk analysis approaches, qualitative or quantitative, have been widely used to enhance maritime safety in recent years, they have been insufficiently utilized in the PSC inspection area in the literature.

Meanwhile, the PSC system has experienced several changes in ways both large and small since it came into effect. However, none of them equalled the one in 2011. The change of inspection regime delivered a message to the world that sub-standard vessels are no longer tolerable in the regions and with the new refusal of access measures in place, repeated offenders will be banned from the ports. Hence, it is necessary for us to analyse whether the introduction of NIR has had such a remarkable influence on PSC inspections as expected.

In this thesis, a comprehensive analysis on PSC inspection is conducted. First, based on the Paris MoU inspection records, the factors influencing the inspection results and the regulations of port authorities are identified. Second, several approaches are applied to accomplish our work, including Bayesian Network, TAN learning, gradient descent, game theory and mixed strategy Nash equilibrium solution. Third, the influence brought by NIR on PSC inspection system is clarified through a comparative analysis in this project. Fourth, the framework of this research aims at developing a real-time risk prediction tool and a decision-making tool for port authorities under dynamic situations. Finally, the proposed models are validated by an empirical study to demonstrate their practical significance

1.2 RESEARCH OBJECTIVES

The aim of this research project is to develop a novel methodology incorporating BN and game theory to propose a dynamic prediction tool to determine the detention rate for port authorities and ship owners, analyse the impact of the implementation of NIR on PSC inspection, as well as help port authorities in decision-making when regulating the inspection policy. The results of the research will provide important insights for port authorities to ensure that optimal inspection actions are taken to improve safety at sea in a cost effective manner.

To achieve the aim, the integrated objectives are defined as follows:

1) Review the risk assessment and decision-making techniques that have been widely applied in maritime safety and PSC inspection, particularly those capable of dealing with unavailability and incompleteness of risk data.

2) Distinguish the different data-driven approaches to construct BN structure.

3) Develop a risk assessment model using BNs to reveal the degree of importance of different risk factors influencing PSC inspection results in different periods, as well as predict the detention rate of individual vessels under dynamic situations.

4) Clarify the influence of the implementation of NIR on PSC inspection results through a two-part comparative analysis. One is the macro-level analysis based on the historical inspection records obtained from the Paris MoU, the other is the micro-level analysis between 'Pre-NIR' BN model and 'Post-NIR' BN model proposed in this research.

5) Develop a risk-based game model based on the outcomes from BN models to determine the optimal inspection strategy of port authorities under different circumstances after the implementation of NIR.

6) Propose a decision-making framework for port authorities to help them make optimal and rational inspection decisions based on the dynamic prediction tool from BNs and the optimal Nash solutions from the game model.

1.3 RESEARCH QUESTIONS

The designed analytical logic follows the related questions of 'what to model', 'how to model' and 'how to analyse and improve' PSC inspections. In this regard, the research questions are showed as follows:

- Q1.What are the factors influencing the result of a PSC inspection?
- Q2.How to quantify the relationships between different risk factors and the inspection results, as well as the influencing degree of these risk factors before and after NIR?
- Q3.How to evaluate the influence of the implementation of NIR on PSC inspection system?
- Q4.How to model the inherent relationships between port authorities and ship owners when executing a PSC inspection efficiently and accurately?
- Q5.How can the risks and uncertainties hidden behind the relationships between port authorities and ship owners in a PSC inspection be quantified?
- Q6.What are the suggestions and strategies provided to help port authorities when making decisions during a PSC inspection?

1.4 RESEARCH STRUCTURE

Chapter 1 introduces the basic information of the research, including the background, objective, framework, novelty and contribution. This brief introduction outlines the whole research project, and demonstrates the necessity of conducting this research.

Chapter 2 reviews the related works in this field. Among the risk assessment approaches that have been applied in maritime safety, BN shows its superiority over other approaches from literature and is thus selected as the method to analyse the risks in PSC inspection. In order to construct the BN objectively, different data-driven network construction approaches are summarized from the past studies. Additionally, the application of game theory in transportation is also revealed.

Chapter 3 develops two data-driven BN models of PSC inspection system based on the Paris MoU online inspection database, one is 'Pre-NIR' BN from 2005 to 2008, the other is 'Post-NIR' BN from 2015-2017. The sensitivity analysis of the models reveals the degree of importance of different risk factors influencing PSC inspection results in different times. Further, it is applicable that the BNs can serve as the risk prediction tools for port authorities to make decisions in a cost effective manner under dynamic situations.

Chapter 4 clarifies the influence of NIR on PSC inspection results. Through the comparative analysis on two BN models and the statistics derived from the Paris MoU annual reports, the influence of NIR is proved significant and positive. The changes brought by NIR has transformed the PSC inspection system a lot, making NIR act as a big step in the Paris MoU history.

Chapter 5 develops a risk-based model to determine the optimal inspection strategy of port authorities after the implementation of NIR. The components and parameters required to build the game model are identified from previous related works and the 'Post-NIR' BN model. The Nash solution of the game model eventually reveals the theoretical optimal inspection policy for port authorities under different circumstances.

Chapter 6 illustrates the optimal inspection policy of port authorities by an empirical study. Through analysing the optimal inspection rates of bulk carriers under different situations, several research implications are derived. In addition, it comes up with some suggestions for port authorities to help them make optimal decisions during PSC inspections, as well as a decision-making framework to help port authorities make rational and optimal decisions under NIR.

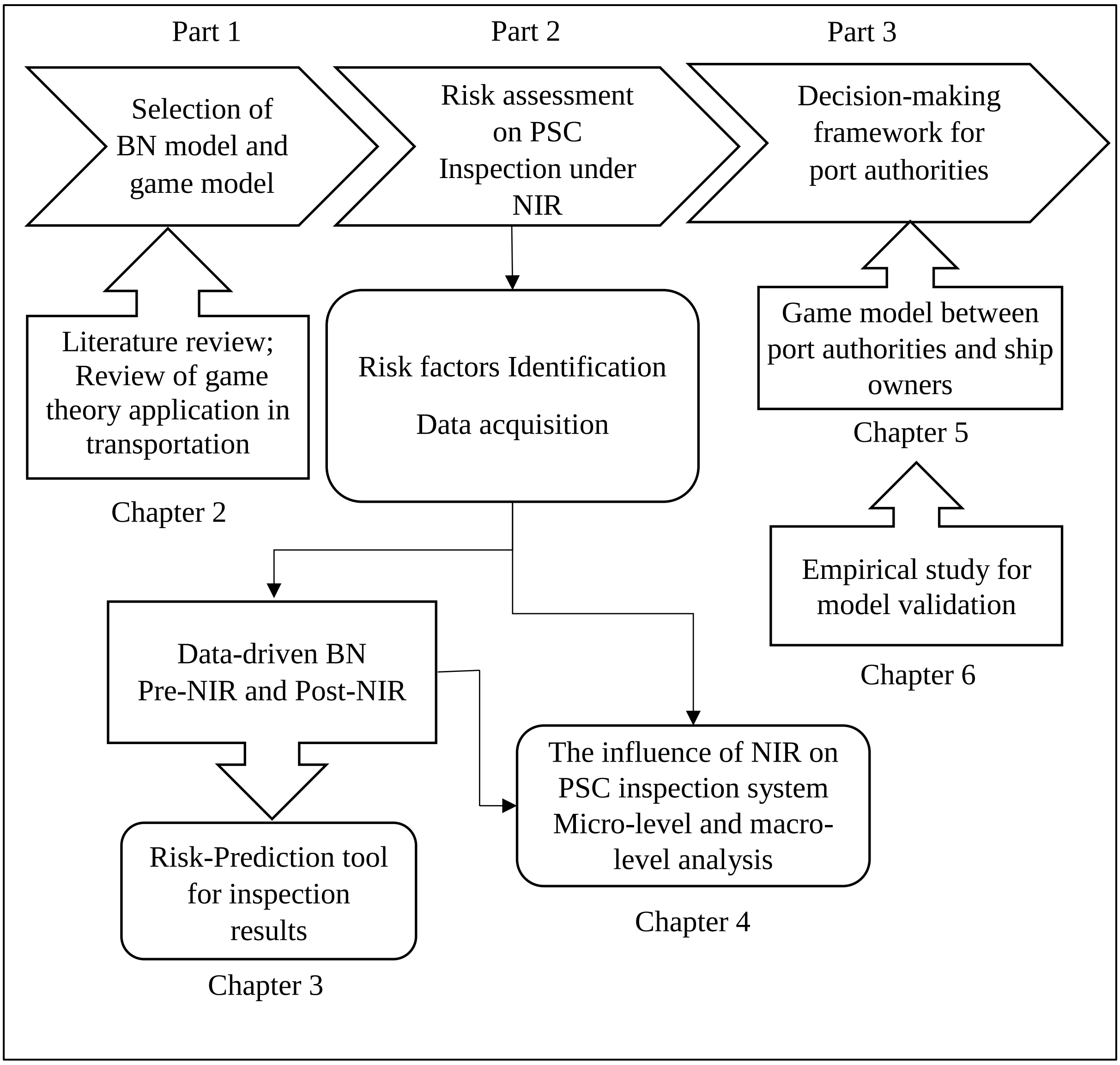

Figure 1.4 Research Structure

(Source: Author)

1.5 RESEARCH CONTRIBUTION

This research provides important insights and contributions for port authorities and ship owners, both academic and industrial.

Academic contributions

1) In this research project, the risk assessment model of PSC inspections is constructed completely from objective data, which is different from former risk assessment research in this area that is based on subjective data (Expert judgment) or a combination of subjective and

objective data. The application of objective data-driven network construction approach provides a new way to build risk assessment model for researchers in PSC inspection area.

2) The incorporation of BN and game theory exploits a rational and novel way to quantify the relationship between port authorities and ship owners. Meanwhile, the application of BN to represent the uncertainties and risks existing in the game model highlights another contribution to the academic field.

3) To the authors' best knowledge, since NIR went into effect in 2011, company performance is, for the first time, viewed as an important factor influencing the decisions of port authorities in PSC inspection practice and scientific research.

4) Unlike the risk assessment research on PSC inspections before, the methodology applied in this research project is advanced and comprehensive. Compared to the most used methods in this area, i.e. risk matrix, the risk-based game model method can explore and analyse the PSC inspections more thoroughly, developing a new idea to conduct research on PSC inspections.

Industrial contributions

1) The proposed BN model can served as a dynamic risk analysis and prediction tool in PSC inspection. For port authorities it is used to ensure that optimal inspection actions are taken to improve safety at sea in a cost effective manner; and for ship owners it works as an early-warning system to identify and address the potential deficiencies of the vessel in advance.

2) The proposed optimal inspection policy from the game model is able to provide real-time PSC decisions for port authorities in dynamic situations accordingly, where the risks constantly change.

3) The influence brought by NIR is clarified through a comparative analysis between 'Pre-NIR' period and 'Post-NIR' period from two different perspectives. The results indicate the introduction and implementation of NIR is proved reasonable and significant to PSC inspection system. This positive revolution has transformed the whole system a lot.

4) Suggestions are proposed to help port authorities of different economic constrains to make rational decisions. For instance, when a port authority has limited economic constrains, it should choose the optimal inspection rate as suggested by the game model; otherwise it can

increase the punishment to an appropriate level as suggested by the model, to tackle the sub-standard effort and illegal actions of ship owners.

Further, the decision-making framework could play an important role in helping port authorities to make rational decisions under different environments and constraints.

CHAPTER 2 LITERATURE REVIEW

This chapter reviews corresponding works related to the research topics. Among the risk assessment approaches that have been widely applied in maritime safety, Bayesian network has proved the most appropriate one for PSC inspection research from literature. Additionally, the existing data-driven approaches for BN construction are summarized and described as well. Another major methodology applied in this project, game theory, also shows its diversity and significance when applied in the transportation field.

2.1 RISK STUDIES ON MARITIME SAFETY

Maritime safety analysis is essentially a process of utilizing formalized approaches for the quantification of risks in probabilistic terms. Actually, in the past decades, the way of quantifying risks in the maritime industry has undergone great transformation. Among the early work on risk assessment in maritime safety, qualitative analysis was largely used (Lee & Sanquist, 2000; Sii et al., 2001; Vieites et al., 2004). For instance, in a score method, the selected evaluation factors are scored according to subjective experience. It provides the basis of the target factor method employed by the Paris MOU and the Tokyo MOU. Meanwhile, most research in this academic field was based on the accident statistics (Fowler & Sørgård, 2000; Soares & Teixeira, 2001), showing great influence on the maritime safety management and providing significant practice for the industry.

However, over the years researchers realized that it is hard to achieve the best risk assessment results by qualitative or quantitative analysis separately. The former way to assess maritime safety was inadequate to cope with the uncertainty in data, resulting in partial and impractical consequences. Fuzzy comprehensive evaluation (Akhtar & Utne, 2014; Pillay & Wang, 2002), grey system theory evaluation (Deng, 1989), neutral network evaluation (Li, et al., 2000), evidential reasoning (Liu, et al., 2004; Wang, et al., 2006), data environment analysis model (Wu, et al., 2015), Monte Carlo simulation (Goerlandt, et al., 2012; Montewka, et al., 2010), Markov chains (Kolowrocki & Soszynska, 2011), genetic algorithm (Montewka, et al., 2010; Nwaoha, et al., 2011; Nwaoha, et al., 2013) and some other risk assessment approaches are gradually used to complement qualitative analysis in maritime safety studies. Meanwhile, risk analysis is moving away from accident investigation to the analysis of risk factors, resulting in the creation of advanced methods on risk diagnosis and prediction, such as BN (Eleye-Datubo, et al., 2006; Eleye-Datubo, et al., 2008; Ren, et al., 2009).

It is noteworthy that the fast development of maritime safety analysis since the 1990s is attributed, at least in part, to the adoption and approval of Formal Safety Assessment (FSA) by the IMO. FSA can be described as a systematic method of enhancing maritime safety that is done through a careful process of risk assessment and evaluation. The IMO defines FSA as a 'rational and systematic process for assessing the risks associated with shipping activity and for evaluating the costs and benefits of reducing the risks'. It is of great importance to the marine industry because 1) It helps make a transparent decision-making process; 2) It helps justify the candidate measures selected through this process 3) It ensures the decision is the best choice under a particular situation after a thorough understanding and comparison of all other available options. Given this, a large number of publications and a large amount of literature relating to FSA application on maritime safety have been published in recent years, including risk estimation of maritime transportation (Yang, et al., 2008), decision-making of maritime administration (Yang, et al., 2009), maritime security (Yang, et al., 2012; Yeo, et al., 2013), and the threat of terrorism and piracy (Pristrom, et al., 2013).

Besides the risk assessment approaches applied in maritime safety, the topics in maritime safety also changed greatly. In the 1990s, the research orientation focused on the safety of individual vessels (Stiehl, 1977), and their structure and designs (Guedes Soares, 1997; Guedes Soares, 1998). Pate-Cornell (1990) conducted a probabilistic risk analysis research considering organisation aspects to describe the relationship between the component failures and the offshore system safety. However, after entering the 21st century, the topics in maritime safety area have presented its diversification.

Ship navigation safety showed an upward trend among these topics (Chen & Fang, 2005; Fang & Hu, 2006; Chen & Fang, 2009). Through the model based on the relative risk assessment (MRRA) approach, Hu et al. (2007) put forward a novel model considering the detailed information about accident characteristics to assess the pilotage safety in Shanghai, China. Consequently, it was proved that the model is useful to solve the problems in the risk assessment of ship navigation safety in practice.

Being supported by a large number of different risk assessment approaches, vessel collision is another hot topic in this field. In order to acquire a thorough description of the influences on collision causation probability of different risk factors, Hanninen & Kujala (2012) proposed a Bayesian belief network (BBN) model on the Gulf of Finland. The results indicated that changing course played the dominating role in a vessel encounter situation. Similarly, Merrick

& van Dorp (2006), Hu et al. (2008) also applied BNs to analyse the influence of safety variables on vessel collision probabilities in San Francisco Bay and Shanghai Harbour, respectively. In 2012, Montewka et al. (2012) defined a new, proactive BBN model for estimating the consequences of vessel collisions. Additionally, Monte Carlo Simulation (Montewka, et al., 2010; Goerlandt, et al., 2012), Fuzzy method (Celik & Akyuz, 2018) and FSA (Endrina, et al., 2018) showed their ability when analysing the vessel collisions.

Evidence showed that 80–85% of the recorded maritime accidents are directly caused by human error or attributed to a degree to human error (Harati-Mokhari, et al., 2007), indicating most risks and hazards in maritime transportation are closely related to human and organisational factors, i.e. misjudgement of pilot, lack of communication and inattention of pilot. It is widely recognised that human elements play the major role in most accidents involving modern ships, for example, oil tanker grounding (Ung, 2018), maritime grounding (Akhtar & Utne, 2014), maritime environmental pollution (Celik & Akyuz, 2018) and maritime operation problem (Lin & Tsai, 2014). Despite this fact, studies on human factors started relatively late and remained at a level of qualitative analysis with much focus on the training of seafarers and enforcement of the associated regulations of a prescriptive nature. Efforts in the pioneering work in this field started in 2008. Trucco et al. (2008) presented an innovative approach combining the BBN model and fault tree analysis (FTA) to integrate human and organisational factors into maritime risk analysis. The approach has been applied to a case study in the maritime industry, and eventually utilised in many other sectors. Other works, like Martin & Maturana (2010), El-Ladan and Turan (2012), Chauvin et al. (2013) and Yang et al. (2013), were also considered significant in guiding this new research direction in the maritime safety field.

It is interesting to see that a much broader range of topics have been studied in the recent decades, e.g. policy evaluation & recommendation, spill & pollution (Goerlandt & Montewka, 2014), vessel structure (Montewka, et al., 2017), and safety culture, indicating that researchers are trying to protect maritime safety from many different perspectives.

2.2 RISK STUDIES ON PSC INSPECTION

Since PSC inspections play an increasingly important role in maritime safety, more and more researchers have conducted related studies from both qualitative to quantitative perspectives. Various risk assessment approaches have been developed and applied in the past decades, demonstrating the diversity of this research field.

Kasoulides (1993) stressed how flag state enforcement has diminished in the face of the proliferation of open registries and why coastal states have reacted by asserting their rights through the resultant regime of PSC at the regional level. Similarly, Bell (1993) did a study analysing the nature of flag and port state control in the UK, a comparison between two inspection forms indicated that the effectiveness of PSC required to be improved not only in the UK, but also in Europe, and even throughout the world. Based on the view from practice, Kiehne (1996) focused on the sanctions available to PSC authorities in respect of the foreign ships being inspected, ranging from instructions to rectify deficiencies (i.e., with immediate effect before departure, within two weeks, or at the next port of call) to outright detention. The sanctions that port authorities have should help them eliminate the operation of substandard vessels in the ports of Europe. In 2001, Özçayır (2001) reviewed the practice of PSC in different jurisdictions and pointed out the issues existing in the practice of European PSC, such as the pivotal role of the ISM Code and the function of classification societies. Chiu et al. (2008) investigated the implementation of the PSC system in Taiwan and further discussed some in-depth issues about the system including the difficulties of the implementation and the inadequacies of the system. Chang (2001), Chiu & Chiou (2005), Chiou (2006) did similar research.

Payoyo (1994) assessed the PSC regime by analysing inspection statistics generated by the Paris MoU from 1982 to 1992. Although substandard vessels still posed a threat to maritime safety, the inspection regime achieved several significant accomplishments such as the collection of baseline data on substandard ships in the region, increased effectiveness in the enforcement of international standards, and closer regional cooperation resulting in the more efficient employment of maritime safety enforcement resources. This conclusion was sound in line with the work conducted by Mejia (2005). As one of the first contributions on the effectiveness of PSC, Owen (1996) described the practice of PSC in the Paris MoU in detail and discussed the limitations inherent in the PSC regime connected with the fact that the port state has no direct influence over the design and construction of vessels that are being inspected. One year later, Hare (1997) showed how the proliferation of regional MoUs has significantly diminished the potential for substandard ships to participate in international commerce. In 2000, McDorman (2000) examined the contribution of regional PSC agreements and harmonized inspection procedures, and then pointed out that the playing field among different ports has been improved.

When entering the 21st century, the studies related to PSC were restricted to not only qualitative analysis, but also quantitative analysis. However, use of quantitative risk approaches in PSC was limited to risk diagnosis, waiting for new solutions on real time risk prediction to be explored.

Shen & Chen (2003) and Yang (2004) both proposed risk assessment PSC systems, which had been proved to have better performance than traditional PSC inspection mechanisms. Knowing that intense maritime traffic may cause significant navigational challenges in the Istanbul Strait, Kara (2016) applied a weighted point method to assess the risk level of each vessel experiencing the PSC inspection under Black Sea MoU. However, the weighting and scoring methods adopted in these studies are in large part based on subjective expert judgements, which may cause arguments on the results.

Avoiding subjectivity in weighting has been extensively studied. Xu et al. (2007) presented a risk assessment system based on support vector machine to estimate the risk of candidate vessels according to historical data before conducting on-board inspections. Evaluations showed that the proposed system could improve the accuracy of risk assessment. Furthermore, Gao et al. (2008) combined support vector machine and K-nearest neighbour approaches to develop a new risk assessment model capable of coping with noisy data. Consequently, this method significantly improved the accuracy of the results. Although showing attractiveness, such methods still reveal problems in their practical applications in tackling dynamic risk prediction (e.g. ship detention probability) in different environments. This problem hinders the practical contribution of risk assessment approaches in PSC inspections. To solve this issue, Yang et al. (2018) utilized the BN to develop a detention rate prediction tool for port authorities. The advantages of BN over other risk assessment approaches in dynamic prediction provides important insights for us to seek the optimal inspection policies under different environments in NIR. However, Yang et al. (2018) only addressed risk analysis and did not conduct further studies on how the dynamic risk results can realise the optimization of inspection policy making of port authorities in PSC.

Collected from the Swedish maritime administration database, Cariou et al (2008) used 4,080 observations in 1996 – 2001 to build Poisson models to test the effectiveness of PSC. The estimation showed that some vessels' characteristics (e.g. vessel age, vessel type, vessel flag) have significant influence on the number of deficiencies detected during PSC and length of time between two successive PSC inspections. Subsequently, the analysis also pointed out that following a PSC inspection, the reported deficiencies during the next inspection are reduced by 63%, demonstrating the effectiveness of PSC in controlling vessel safety.

Based on 183,819 PSC inspection records, Knapp & Franses (2007) applied binary logistic regression to measure the effect of inspections on the probability of casualties, especially for the very serious cases. Meanwhile, the model determined the magnitude of improvable areas for substandard vessels. Later in the same year, they did a further econometric analysis about the influence on the detention probability of different risk factors, and the results indicated only vessel types and PSC regimes were influential elements. Knapp & Franses (2007) incorporated quantitative risk analysis to ship inspection to improve its effectiveness. The studies revealed that the age of the vessel, ship type, and flag of registry appear to be significant predictors.

In 2014, Li et al. (2014) built a bi-matrix game between the port authorities and ship operators in PSC inspection to decide on the optimal inspection policy with an aim to save costs on inspection whilst keeping deterrence pressure on potential wrongdoers. Through a numerical case study, it is shown that the optimal inspection rate obtained from the model can yield a significant saving, as well as prevent potential violations by ship operators.

In general, the research on PSC inspections has developed towards a diverse and popular academic research field. More approaches, whether qualitative or quantitative, have been applied to a broader range of topics, showing that PSC inspection is attracting more and more attention.

2.3 BN IN MARITIME SAFETY AND PSC INSPECTION

Taking advance of causal inference, BN can be used to analyse the degree of importance of risk factors and the relationships between them. Compared to pure Bayesian theory, BN is more visualized; while compared to other graphic models, it has a foundation of mathematical knowledge. Because of its advantages, BN has been increasingly applied in maritime safety in the past decade. When summarizing the topics of the publications in this area, it is not surprising to find various aspects are covered.

2.3.1 The occurrence of ship-ship collisions

As mentioned above, collision is one of the major types of maritime accidents around the world. It has two forms: one is the collision between one vessel and a floating or still object such as an iceberg, the other is the collision between two or more vessels. In local sea areas with high traffic intensities, such as the Gulf of Finland and the Singapore Strait, ship–ship collision is one of the most frequently occurring accident types (Kujala, et al., 2009; Weng, et al., 2012; Klanac, et al., 2010).

Goerlandt & Montewka (2015) proposed a framework for risk analysis of maritime transportation systems. In order to quantify the probabilistic risk, BN was used to form the model serving as an evidence assessment tool. Through applying to a case study of an oil tanker ship-ship collision in the Gulf of Finland, the model was proved plausible. From a different angle, Hänninen & Kujala (2012) utilized BN to estimate the role of human factors on ship collision probability in the Gulf of Finland for discovering the variables with the largest influences and for examining the validity of the network. Changing course in an encounter situation is the most influential variable in the model, followed by variables such as the situation assessment, danger detection, personal condition, maintenance routines and the officer's fatigue. Later in 2014, they further presented an expert knowledge-based preliminary assessment of how the deployment of Enhanced Navigation Support Information navigation service would affect the ship collisions and groundings in the Gulf of Finland. The result was positive, as the implementation of the system effectively decreased the number of accidents. The proposed model can be updated and improved when more evidence is available and the service is widely used (Hänninen, et al., 2014).

2.3.2 Navigational risk analysis

With increased vessel traffic, it is imperative that any potential obstacles to navigation should be assessed in advance. Hazards to the crew, the environment and social assets should be avoided at all times.

In order to improve the navigational safety in the Yangtze River, Zhang et al. (2013) used the FSA concept and a BN technique to estimate the navigational risk of the Yangtze River. A scenario analysis was conducted to demonstrate the application of the model and the way it can improve the navigational safety in the Yangtze River. Similarly, Banda et al. (2016) adapted the FSA into a BN model to manage the risk of winter navigation in the Gulf of Finland. The results indicated that ship independent navigation and convoys are the operations with higher probability of oil spills.

2.3.3 Maritime accidents analysis and prevention

As a quantitative modelling tool, one of the advantages of BN is its function to predict and prevent the maritime accidents. Sometimes this function can even be utilised to help users make decisions under different conditions.

Based on the maritime accident database of the Portuguese Maritime Authority, Antao et al. (2009) selected 857 validated accidents to develop a BBN for maritime accident analysis. The results showed that it is possible to develop a model derived from real data to analyse the influence of major risk factors on maritime accidents, even to support decision-making for maritime authorities.

Hanninen (2014) discussed the contribution of BN to maritime accident prevention and safety modelling, as well as some challenges in real practice. Compared to other dynamic modelling tools, BN is a rather well suited tool for maritime safety management and decision-making. Li et al. (2014) also worked on this topic and reached similar conclusions.

2.3.4 Offshore safety management

The operation of an offshore installation is associated with a high level of uncertainty because it usually operates in a dynamic environment in which technical and human and organizational malfunctions may cause possible accidents. New regulations, such as the EU directive, mirror society’s zero tolerance for offshore accidents. The offshore oil and gas industry has achieved an outstanding improvement in occupational safety over the past three decades. Although it has learned much from major accidents in the past, such accidents are still occurring.

Associated with a high level of uncertainty, offshore safety is another concern that can be solved by BN. Eleye-Datubo et al. (2008) proposed a framework based on fuzzy BN (FBN) to analyse maritime and offshore safety. It acted as a bridge in the probabilistic setting of the domain. Its implementation has been demonstrated in a maritime human performance case study that utilizes performance-shaping factors as the input variables of this groundbreaking FBN risk model. Further, Ren et al. (2009) employed the FBN approach to model causal relationships among risk factors that may lead to possible accidents in offshore operations. The FBN model explicitly represented cause-and-effect assumptions between offshore engineering system variables and made the risk and safety analysis of offshore engineering systems more functional and easier in many assessment contexts. A case study of the collision risk between a floating production, storage and offloading unit and the authorized vessels due to human errors during operation was used to illustrate the application of the proposed model.

2.3.5 Risk based vessel design

Considering the drainage and leakage of fluids during the process of vessel design, Lee & Somemerfeld (1994) developed some equations related to the drainage times for a variety of geometrical vessel shapes, which can be used as the guidelines for shipyards in the design of vessels to reduce the risks and hazards when sailing on the sea.

Yuan & Wang (2010) applied both the Monte-Carlo method and the stochastic method to study the structural reliability of the pressure vessels. The combination of two methods was efficient and practical, leading to an accurate numerical simulation that can help make the vessel design more reasonable.

In order to analyse the effect of global design factors (e.g. ship motion, body vibration) on the human performance, Montewka et al. (2017) introduced a BBN to link the effect of these factors with the human performance suitable for the process of vessel design. Validated by the promising results, the model was useful for facilitating risk-based ship design for naval architects and vessel designers.

2.3.6 Oil spill in maritime accidents & oil spill recovery

Oil spill accidents have been one of the major concerns of maritime industry for a long time. They are commercial and environmental catastrophes that may cause huge losses to the society, e.g. the Gulf of Mexico oil spill. Because the accidents involve vessels or oilrigs, the ocean water becomes contaminated by liquid petroleum hydrocarbon, causing damages to the environment taking decades to recover. In addition to killing fish, marine mammals and birds, oil spill accidents will destroy beaches and wildlife habitats as well. When an oil slick reaches the beach, it also affects human settlement on the beaches and mangrove forests. Moreover, it takes months-long oil cleaning operations to bring back the areas around the accident back to normality.

Due to limited data, Goerlandt & Montewka (2014) proposed a BN model for reasoning under uncertainty for the assessment of accidental cargo oil spill in ship-ship collisions from product tankers. It provided a platform to assess the uncertainty about the possible oil outflows in maritime traffic scenarios, as well as enabling an insight into the probabilistic nature of possible oil outflows conditional on the impact conditions.

From another perspective, Lehikoinen et al. (2013) developed a BN to examine the recovery efficiency and optimal disposition of the oil spill accidents in the Gulf of Finland, and the process seemed to be strongly controlled by certain random factors independent of human actions, e.g. wave height.

Besides the above-mentioned topics, there are still other research orientations that should be paid more attention. For example, the wastewater treatment (Bagley David & Sahely Brian, 2001), sea wave overtopping issue (Tolo, et al., 2015), etc. The variety of topics indicates the popularity of BN in the maritime safety area and the expansion of the range of topics will continue.

However, few researchers investigated its effectiveness and potential in analysing the risks relating to PSC inspections. Hänninen & Kujala (2014) explored the dependencies of PSC inspection findings and vessels' involvement in accidents and incidents by using two learning algorithms to train BNs based on inspection, accident and incident data. The results showed that vessel type, inspection type and the number of structural conditions related deficiencies are among the most important factors influencing accident involvement. Later in the same year, Hanninen et al. (2014) presented another BN model to analyse the maritime safety management. According to the model, some sub-areas of maritime safety management, for example, the Port state control, still have room for improvement. Further, a good IT system would be beneficial for PSC inspection.

Focusing on the increasing threats from smuggling by sea, Wen et al. (2016) applied classification trees and Bayes algorithms to improve the recognition rate of smuggling vessels. The paper presented a selection method for vessels that could not only be applicable in smuggling activity, but also in other maritime instances, for example, PSC inspection.

In addition, Yang et al. (2018) proposed a data-driven BN model involving multiple risk factors, to analyse their individual and combined effect on PSC inspections, and to develop a real-time prediction tool for port authorities to rationalize their inspections under dynamic situations. The results of the study provide important insights for both stakeholders to ensure that optimal inspection actions are taken to improve safety at sea in a cost effective manner and check whether their actions are beneficial.

However, such studies focused on the PSC inspection system before the implementation of NIR, meaning the influence of company performance on inspection results is overlooked. As an important factor in new PSC inspection system, company performance is introduced when building BN for PSC inspections in this study. Furthermore, none of them had ever undertaken further studies to look at how the dynamic risk analysis result can assist port authorities in the development of rational inspection policies in their PSC practice.

2.4 CPT CALCULATION APPROACHES IN BN

Despite such applications, a common criticism of BN is that it requires too much data in the form of prior probabilities, and such data is hard to collect, even inaccessible sometimes (Yang, et al., 2008). Meanwhile, the size of the conditional probability table (CPT) grows quickly in size as more parent nodes are added, leading to complexity and difficulty in computation. Normally the traditional way to obtain the CPT is to calculate the frequency directly from the data. Nevertheless, the scarcity of empirical data makes the work impossible to achieve sometimes. In addition, Gaarder et al. (1997) pointed out that statistics describe only the past, which may not be of much use in predicting the occurrence probability of an event happening in the future. Due to these reasons, CPTs are often generated based on experts' judgements in many publications. Mkrtchyan et al. (2015) analysed the BBN uses for human reliability analysis applications. During the process for building the model, expert judgment is utilized in the assessment of the CPTs of the model.

However, there also exist some problems in terms of using the subjective probability provided by experts. Experts may fail to take into consideration every condition with respect to human errors (Slovic, et al., 1979), as well as being restricted by their professional mode of thinking and corresponding experience (Skjong & Wentworth, 2001). Meanwhile, for large-scale BN models, the use of expert judgment is time-consuming, impractical and inconsistent (Mkrtchyan, et al., 2015).

To address such concerns, Wettig et al. (2005) and Rijmen (2008) both introduced the logistic regression techniques to calculate the conditional probabilities of BN for discrete variables. Li et al. (2014) further improved the approach through combining the logit model and binary logistic regression to generate a relative risk score covering most of the world vessels. This safety index was provided as an important input for constructing a BN model for maritime risk analysis (Li, et al., 2014). However, it is available only when a large dataset is obtained.

Another approach is called Noisy-OR. Through the Noisy-OR approach, the elicitation of full CPTs is simplified to the assessment of individual parent-child Conditional Probability Distributions (CPD) while the missing relationships are derived by combining the estimated CPDs disjunctively (Pearl, 1988). It was originally proposed by Pearl in 1988 and experienced several extensions (Diez, 1993; Onisko, et al., 2001). Yang & Ning (2007) proposed non-impeding noisy-AND tree and improved it later in 2012, which enhanced BN's capability of dealing with multi-state and dependent nodes. Yet, its limitations on how to derive the tree topology and the fact that not all causal interactions can be expressed by the method affects its popularity (Xiang, 2012; Xiang, et al., 2011; Xiang, et al., 2009).

Through applying ranked nodes to BNs, Norman et al. (2007) presented a novel but effective approach. The approach is based on the doubly truncated Normal distribution with a central tendency that is invariably a weighted function of parent nodes. The results of case studies proved that the elicitation burden is much reduced by using ranked nodes. It is naturally an evolutionary approach of expert judgments.

By incorporating Monte Carlo simulation with expert judgment, a novel way to learn BN has been proposed in recent years to avoid the elicitation of prior distributions. Involving Markov chain Monte Carlo simulation, Tebaldi & West (1998) applied the method when analysing the network traffic flow. The explored model was able to cope with the uncertainty in route selection and provide specified route choice probabilities. Cano et al. (2011) explained this method in detail and validated the model through alarm networks. Gui et al. (2011) applied this method to investigate the impacts of time and weather on animal-related outages in overhead distribution systems. From the literature, it is not surprising to find the application of Monte Carlo simulation in learning BN is widely applied in many disciplines, e.g. electrical industry (Torres & Santos, 2006).

Other approaches, like interpolation of anchor inputs (Cain, et al., 1999; Wisse, et al., 2008), function based methods (Vinnem, et al., 2012), and expectation maximization (EM) (Attias, 2000; Sun, et al., 2006; Nessler, et al., 2013) also provide different ways to cope with the drawbacks of BN in terms of high demand on prior probabilities.

2.5 DATA-DRIVEN APPRAOCHES TO CONSTRUCT BN

Normally, the structure of a BN is constructed using human expert knowledge or common sense. However, this type of approach is time consuming, and heavy emphasis is placed on experts to provide both the local probability parameters and dependency among the parameters. An alternative approach for BN construction is to induce the network structure from data, namely the data-driven approach, which can greatly reduce the dependence on human experts and in some cases increase the accuracy of the model. However, the primary drawback of the data-driven approach is that the number of possible structures for a given problem grows super-exponentially with the number of employed variables in the problem domain. For a problem consisting of *n* variables, Robinson (1973) calculated the complexity of the search space and provided a formula to compute the number of possible BN structures for various values of *n*. The table below lists the possible number of structures for each value.

Table 2.1 The number of possible BN structures

n	*Number of BN structure*
1	$1.0*10^{0}$
2	$3.0*10^{0}$
3	$2.5*10^{1}$
4	$5.4*10^{2}$
5	$2.9*10^{4}$
10	$4.2*10^{18}$
20	$2.3*10^{72}$
50	$7.2*10^{424}$
100	$1.1*10^{1631}$

(Source: New Directions in Graph Theory, 1973)

To reduce such complexity, a large number of algorithms and efforts have been proposed, however the problem remains complex and hard (Chickering, et al., 1994). Given that the number of possible structures for a given problem domain grows super-exponentially, exact and exhaustive approaches for BN learning become unfeasible. Many algorithms can be found in the literature, which can be classified into two broad categories: 1) dependency analysis approach and 2) search and score approach.

Dependency analysis, which is based on performing conditional independence (CI) test on tuples of variables, was developed by Spirtes et al. (1991) and improved by Cheng et al. (1997; 1997) and Thomas (2005). Through statistical tests or information theoretic measures (e.g. mutual information), the approach can determine whether the relationships between variables in the network are independent or not. Based on an iterative process, the final relationships between each pair of variables are confirmed, thus the optimal BN structure is generated. However, Singh & Valtorta (1995) reported three drawbacks of this method: 1) extensive testing of independence relations to derive the final network structure; 2) CI test relies on an enormous volume of data when condition sets are large; 3) it is unrealistic when the given domain grows exponentially as the number of variables grows. Although there exist several drawbacks, it is still recognised as a good attempt to deal with computational complexity problems in network construction. In order to improve the efficiency of the approach with sparse networks and limited data, Spirtes and Glymour (1991) developed a new CI based dependency analysis algorithm.

Unlike the dependency analysis approach, the search and score approach is more popular and presents a better result. It seeks to explore a search space of candidate BN structures for the one that best represents the causality and dependency relationships. In other words, the approach aims to discover the probabilistic dependency network that most likely generated the data set (Cooper & Herskovits, 1992). It is more like an optimization problem in nature. It consists of three components: search engine, search space and scoring function. In contrast to the dependency analysis, the search and score approach employs a search heuristic to search the space of the candidate structure solutions for one that maximises the score by making perturbations to the solution. The search continues until an optimal solution is found or some predefined stopping criterion is met.

Many search engines have been proposed to do the search work, and can be divided into two categories: sequential algorithms (those that iteratively build upon a single network structure) and population based algorithms (those that develop a series of possible network structures in parallel).

Sequential algorithms

Cooper and Herskovits (1992) derived K2 scoring metric based on Bayes theorem, starting with an empty network and iterating through each node to get the best structure. An assumption for this algorithm is that it requires an order among the variables. If one node A comes before another node B in the ordering, then B can have A as its parent but not conversely. For each node, K2 search heuristic first assumes that a node has no parents, and then adds incrementally the parent nodes that can maximise the probability of the resulting structure. When there is no single parent that can increase the probability, the algorithm stops adding new parents to this node. By parity of reasoning, the parents of all nodes can be obtained, resulting in the final BN structure. The main drawback with this algorithm is the order required. Different order will lead to different network structure. In some cases if the domain knowledge is not sufficient, the quality of the network structure is hard to guarantee (Singh & Valtorta, 1995).

In contrast to Cooper and Herskovits, Buntine's (1991)'B' algorithm does not require a variable order. It also starts with an empty structure. A link will be added at the end of each iteration if it can maximize the score and does not lead to a cycle, until the score no longer increases or all nodes in the order have been visited. However, once local optima occurs, the algorithm could not give reasonable results.

By cherry picking the best properties of the algorithm described above, Singh & Valtorta (1993; 1995) combined them and proposed a conditional independence and Bayesian learning (CB) algorithm. It executes in two phases: first, all nodes in the set are linked to form an undirected graph, CI test are conducted to remove the links between adjacent nodes that are unconditionally independent. The remaining links in the graph are oriented to form an order. Secondly, the order derived is fed into K2 to construct the network. The process is iterated until the termination criteria are met.

Population based algorithms

The population-based algorithms, which referred to as 'nature inspired' search heuristics, are loosely relied on systems found in nature. Given the dimensionality and complexity of the BN search space, these nature inspired algorithms operating on groups of candidate structures in parallel are helpful in BN learning. Many of these algorithms have been utilised as search algorithms in the BN structure learning.

Originally developed by John Holland (1992), genetic algorithm (GA) is derived from the principles of Darwinian evolution, and later widely used as a common approach to tackle the optimization problem. From a BN perspective, the strength of GA lies in its ability to evolve near optimal or optimal solutions to complex problems, as well as achieving multiple goals with minimal information and without searching the entire search space (Deb, 2001). However, as the GA is stochastic, therefore sometimes it may result in a network that consists of cycles. To solve this problem, Novobilski (2003) improved the genetic operators that guarantee acyclicity.

Normally, when exploring the entire space of structures, the scoring function associated with the GA is K2 scoring metric (Larra˜naga, et al., 1996). Clearly, the combination of K2 and GA is computationally expensive, thus not appropriate for the current research. Hence, instead of using the K2 algorithm to evaluate the quality of the order, Chain genetic algorithm is applied to making use of chain structure to reduce the computational expense. The reduction mainly reflects at the point that only the chain structure is evaluated rather than the whole order because 'a chain order is a sufficiently good model to local node orderings from which good BN structures can be build' (Kabli, et al., 2007). Kabli et al. (2007) demonstrated that this approach is superior and computationally more efficient to the original GA when learning the structure of BN. In addition, he validated this point of view through conducting several experiments. There are also other similar research on this approach (Larra˜naga, et al., 1996; Larra˜naga, et al., 1996; Larra˜naga, et al., 1997; Novibilski & Kamangar, 2003).

In recent years, a novel application for BN construction from data, named Particle Swarm Optimization (PSO), is seeking to address some of the issues found in data-driven BN construction work. First proposed by James Kennedy & Russel Eberhart (1995), PSO is a nature-inspired and population-based stochastic search and optimisation heuristic. Operated in a continuous and real number space, it requires primitive mathematical operators and minimal use of computational resources such as memory and processing power. Sometimes in order to reduce the calculation work, it can be executed through the codes from computer programmes (Eberhart & Kennedy, 1995). For some certain problems, previous literature has demonstrated that PSO is superior to GA. Petrovski et al. (2004) compared two approaches when applied in medical systems. The results indicated that PSO was a faster way to find the proper solutions than GA and had a higher chance to find the optimal solution to the problem. The same also applied to the design of aircraft (Mouser & Dunn, 2005). Kennedy & Spears (1998) conducted several experiments on different randomly generated problems. The result of experiments proved that PSO was able to find the global optimum no matter what the situations were, however, GA was not that effective. Hassan et al. (2005) focused on another aspect and claimed that PSO was a more computational efficient approach than GA. Throughout the literature, PSO has shown its advantages in many areas recent years, therefore, it is not surprising to find PSO has already been an important approach to learn BN structure.

There are two major PSO-based approaches currently. Based on binary PSO, construct and repair (CONAR) serves to demonstrate that binary PSO can be used as a search heuristic for BN construction and there is no need to specify an order among the nodes. However, it requires expensive validation and repair operators to ensure the integrity of candidate solutions. To alleviate this problem, Restricted Structure (REST) algorithm was proposed. It is an advanced approach of CONAR, which is improved to guarantee generation of only legal solutions, therefore eliminating the need for validation and repair steps compared to CONAR.

Other data-driven approaches, like estimation of distribution algorithms (EDA) (Romero, et al., 2004), Artificial immune system (AIS) algorithm (Castro & von Zuben, 2005), and Ant Colony Optimisation (ACO) (de Campos, et al., 2002; Daly, et al., 2006), also show their ability in coping with some BN data-driven structure learning problems.

In general, data-driven approaches provide important insights in BN construction, as well as more objective and precise results. Although based on large volumes of data, they are still important alternatives to subjective network learning from professional knowledge and experience.

2.6 GAME THEORY APPLICATIONS IN TRANSPORTATION

Game theory, a mathematical tool to study the conflicts and cooperation between rational decision-makers, has become a popular and powerful methodology over the decades. The basic assumptions that underlie the theory are that decision-makers pursue well-defined exogenous objectives and take into account their knowledge or expectations of other decision-makers' behaviour. One reason for the popularity of game theory is that its associated quantitative models and hypothetical examples can help researchers understand real competitive situations better even if the defined situations are unrealistically simplified (Myerson, 1991).

Therefore, it is not difficult to find that many transportation related issues, involving multiple stakeholders, are essentially of conflict and cooperation characteristics, which can be well modelled by the game theory. The applications of game theory in transportation attract the attention of many scholars, forming a connected pool of research with abundant topics, multi-disciplinary knowledge, various transportation modes and novel methodologies. Sorting how such research was developed in this academic field can help scholars better understand the current development of game theory in transportation.

To help the review work, 112 papers are systematically reviewed from 60 academic journals and 13 conference proceedings from 1983 to 2017, covering multiple transportation modes.

2.6.1 Development of research topics

Game theory has been widely applied to stimulate policy making in transportation. Among different transportation modes, road transportation shows a dominating position in terms of use of game theory (Alberto & Alberto, 1995; Hideyuki, 1999; Chidambaram, et al., 2014) and sea transport has taken a back-seat role in this aspect.

Most of the researchers in road transportation focus on transportation network issues. Cost and benefit is always the focus of attention for governments and individuals in road transportation. Bell (2000) proposed a two-player non-cooperative game between the users (e.g. road user and government) in transportation networks. One the one hand, the road user seeks a path to minimise the expected trip cost, on the other hand, however, the government would choose linking performance scenarios to maximise the cost road users have to pay. The Nash mixed strategy equilibrium developed would help to achieve a balance between two entities, as well as measure the performance reliability of the transportation network. Levinson (2005) developed the congestion theory and congestion pricing theory from micro-foundations. Through game theory, it is found that the road congestion depends on the road users' relative valuations of early arrival, late arrival, and journey delay. Further, the congestion pricing would be determined via a cooperation mechanism to minimize the total costs (Levinson, 2015). In order to find out the optimal choice of a fare collection system, Sasaki (2014) considered game-theoretic interactions between the transit agency and passengers for the barrier-free system. The Nash equilibrium revealed the optimal choice of fare collection system, and a comparative static analysis examined how each parameter can affect the choice.

The network design problem is of vital importance to maximize the profit of carriers, especially the hub network design. It consists of two parts: the strategic decision on hub locations, and the operational decision on demand paths. In recent years, many researchers adopted game theory to analyse this strategic problem (Laporte, et al., 2010). Lin & Lee (2010) developed an integral-constrained game theoretic model for time-definite less-than-truckload freight services in an oligopolistic market. The stable Cournot-Nash equilibrium solution of the model indicated that all carriers possess similar dense hub networks, which are robust even with uneven changes happening in the cost structure of carriers.

Normally the roads in a transportation system are viewed as public goods. However, in some countries part of the road system is privately owned. Because of the nature of privately owned roads, the owners have to pay the maintenance cost and make decisions. Hence, how to split the costs of roads among the users is a strategic and tough problem. Sofia (2012) presented a cooperative game model analysing the practical problem of how a privately owned road association can divide the costs for the road network among the members in an efficient and fair way. Making use of the Shapley value, this cost allocation issue therefore has an appealing solution.

Intuitively, the traffic-responsive signal control is the most efficient control policy in public review. However, Evers & Proost (2015) pointed out it is not always consistent. Through a Stackelberg game model, the study proved anticipatory control outperforms traffic-responsive signal control for an intersection of two routes connecting one origin-destination pair because of first mover advantage and externalities. Further analysis on the game model indicated the superiority of anticipatory signal control over other control systems.

Other topics of publications related to transportation networks like the cost allocation (Rosenthal, 2017), Hazardous goods transportation (Chen, 2012), and green transportation (Bae, et al., 2011), also demonstrate the diversity and popularity of game theory application in road transportation.

In the maritime transportation field, inspection games are mainly presented from a quantitative orientation. Avenhaus et al. (1996) pointed out an inspection game is a mathematical model of a situation in which an inspector verifies the adherence of an inspectee to some legal obligation, such as an arms control treaty, where the inspectee may have an interest in violating that obligation. When applied in maritime transportation, Von Stengel (1991) defined it as 'The port authorities try to minimize the impact of such violations by means of inspections that uncover them. A detected violation is costlier to the ship owner than legal behaviour. The resources of the port authorities are usually limited and complete surveillance is not possible. Then, inspections have to be randomized and the inspection game typically has a mixed equilibrium.' Canty et al (2001) and Rothenstein & Zamir (2002) conducted similar research on maritime inspection game.

In order to analyse the policies of PSC inspections, Li and Tapiero (2010) outlined a random payoff game-theoretical framework for vessel inspections at ports considering two kinds of error prone decisions (e.g. detaining a standard vessel or releasing a sub-standard vessel). The authors presented some particular Stackelberg solutions given different scenarios to highlight the effects and the implication of inspection costs and their derivatives. They paid enough attention on the inspections of potentially non-complying ship operators to regulations and sub-standard performance. Based on this research, Li et al. (2015) further developed a game model to decide on the optimal inspection level and the target of the inspection. A bi-matrix game between port authorities and ship owners was built based on the same two types of error prone decisions discussed in 2010. Different from the previous studies, this time the authors generated a Nash equilibrium solution representing the optimal inspection rate for port authorities. A numerical study was conducted to illustrate the optimal inspection strategy, which yielded significant savings for port authorities, as well as prevented potential violations of ship owners. Although showing significant insights for port authorities, there are still several deficiencies existing in both studies , i.e. 1) both studies were conducted before the implementation of NIR, not taking into account company performance as an important factor influencing the decision-making of port authorities in today's PSC practice; 2) when carrying out the numerical studies in the two works, the authors assumed that the work of the authorities was perfect and had no inspection risk exists, which was obviously idealized and thus had limited practical contributions. Hence, when establishing the new game model in this thesis, both the contribution of company performance and the influence of inspection risk on the decisions of port authorities are investigated and considered, highlighting the main differences with and improvements from the two most related papers in the existing literature.

Environmental control problem is another form of the inspection game in transport studies. Bird and Kortanek (1974) explored various theoretical cooperative n-person games in order to aid the formulation of regulations concerning sources of pollutants in the atmosphere subject to the 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. Gueth & Pethig (1990) analysed a signalling game between a polluting firm that could save costs by illegal waste emission and a monitoring agency whose responsibility was to prevent such pollution.

As one of the hot topics in the maritime safety area, the terrorist threat draws the attention of many studies. Baston & Bostock (1991) improved the two-person zero-sum game model derived from Thomas & Nisgav (1976) to address the problem of a patrol trying to stop smugglers who are attempting to ship a cargo of perishable contraband across a strait in one of *m* time units. Meanwhile, a comparison between the two models and the results was discussed. Reilly et al. (2012) used the game theory to model the interactions between a government agency, a carrier and a terrorist. A heuristic solution procedure is constructed to identify effective prohibitions and validated by a realistic case study in the continental US. The model was also suitable for rail network. Sandler & Arce (2003), Sandler & Enders (2003) utilized game theory to model terrorism as well.

Based on the dynamic game theory and agent theory, Yuan (2008) studied the relations among different stakeholders (e.g. the authority, the ship owner and the transportation company) in the safety supervision of dangerous chemicals' transportation. In 2014, Chen & Hu (2014) built a game model between maritime regulators and ship owners to analyse a ship overload problem. Through an equilibrium analysis, the factors that influenced the decision-making of the administrators and the optimal numerical intervals of ship overloads were revealed to help disclose the governance of this issue.

In the other maritime transport related areas, among the game studies are port competition (Ishii, et al., 2013; Song, et al., 2016) and hazardous material transport.

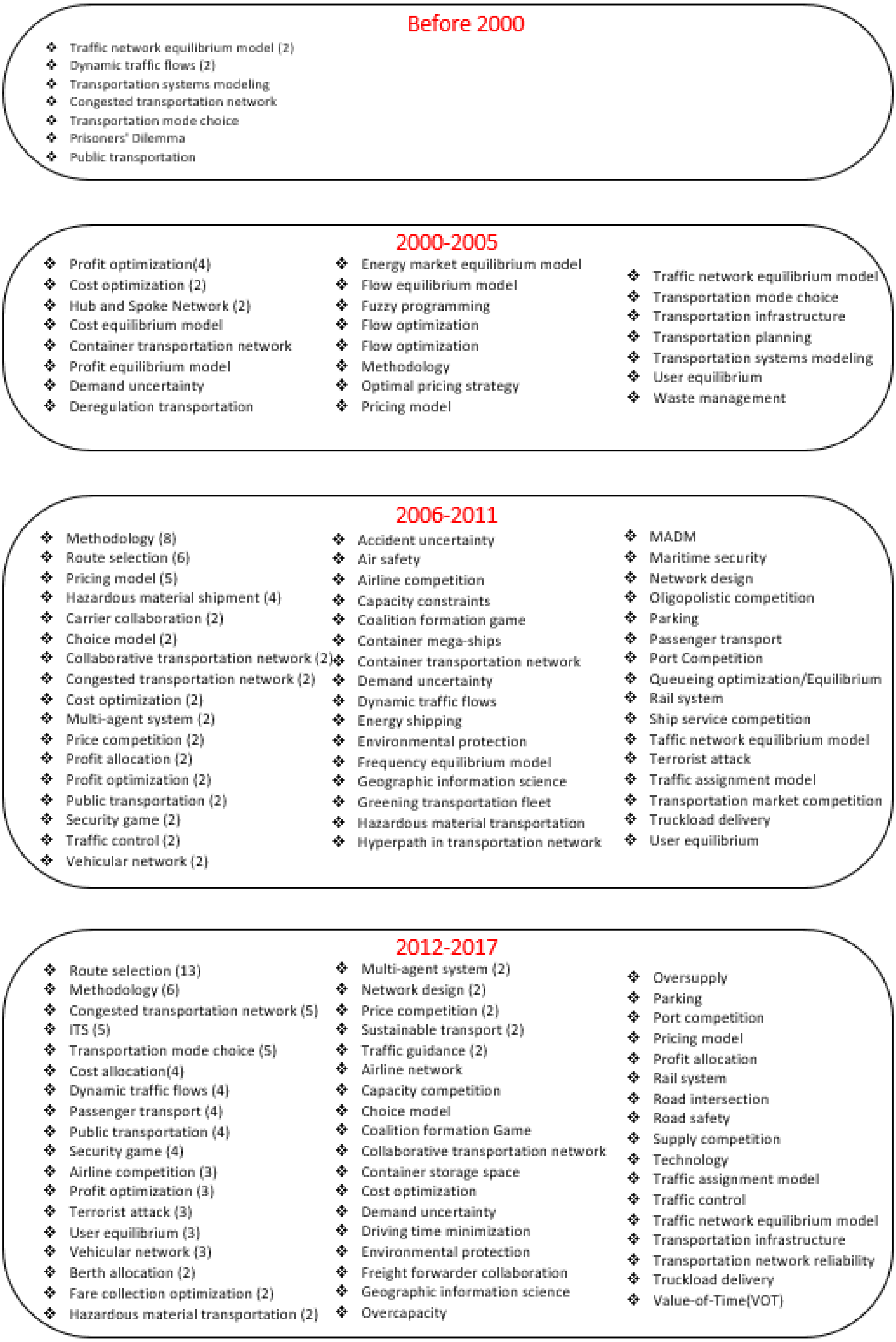

Figure 2.1 Trends of main topics

(Source: Author)

Figure 2.1 shows how the research topics evolved from 1983 to 2017. The number behind each topic is the frequency of occurrence. Before 2000, because of the small number of publications, the topics proposed were limited and paid equal attention, such as traffic equilibrium model and dynamic traffic flows (Wie, 1995). Later profit optimization (Adler, 2001) gradually became the focus during 2000-2005. At this time, the range of topics expanded, indicating more newcomers in this research field.

In the past decade, route selection (Bell, 2006) emerged as the most popular topic, along with some other new-born valued topics such as congested transportation network (Zhang, et al., 2008), passenger transport (Chiou, et al., 2013), collaborative transportation network (Millera, 2011) and transportation mode choice (Saeed, 2013). Some topics, like pricing model (Cardinal, et al., 2009) and hazardous material transportation/shipment (Rahman, et al., 2012), which was among the hot topics in '2006-2011' period, experienced a descending trend during 2012-2017. However, for topics like Intelligent Transportation System (Malandrino, et al., 2012), public transportation (Lodi, et al., 2015) and security game (Baykal-Gürsoy, et al., 2014), things were just the opposite. Besides these major topics, more than 80 other topics have been discussed during this period. The alternation of major topics, as well as the emergence of multiple topics indicates a broader and diverse research field, corresponding to the multi-disciplinary property.

Among these topics, Intelligent Transportation System (ITS) gained increasing popularity. Consisting of advanced technologies, ITS has already been applied to many areas, such as analysis of driver behaviour (Malandrino, et al., 2012), transportation infrastructure construction (Malandrino, et al., 2014) and traffic flow guidance system (Wang & Hu, 2014). As more and more countries have noted the importance of ITS and applied ITS into transportation networks, it will surely become a potential research direction. Meanwhile, the expansion of the range of topics will continue. It is predictable that more and more comprehensive topics are going to appear, i.e. the application of new technologies in transportation systems, risk/safety assessment, novel transportation network modelling approach, and policy evaluation and regulation. Researchers from different research backgrounds are encouraged to cooperate when working on these topics.

The focus of game theory application in transportation varies in different periods, and more and more research topics have been explored and analysed, reflecting the diversity and popularity of the application of game theory in transportation field.

2.6.2 Development of different transportation modes

Table 2.2 lists the evolution of the number of publications of different transportation modes from 1983 to 2017. Transportation mode is categorized into five types: road transportation, air transportation, maritime transportation, rail transportation and general transportation. The first four types are easy to define, but for the last one, it refers to research papers that do not set a specific transportation mode as their targets. For example, the studies focus on transportation network analysis (Schmoecker, et al., 2009; Cardinal, et al., 2009), cooperation and competition between transportation stakeholders of different transportation modes (Audy, et al., 2012; Saeed, 2013), and routing & optimization problem (Crippa, et al., 2009; Krichene, et al., 2014).

Table 2.2 Trend of transportation mode

Transportation mode	Before 2000	2000-2005	2006-2011	2012-2017	Total
General transportation	2	6	12	15	35
Road transportation	2	4	16	31	53
Air transportation		2	3	4	9
Maritime transportation		1	6	4	11
Rail transportation			2	2	4

(Source: Author)

From Table 2.2, road transportation was the most discussed transportation mode, reaching nearly half of the total number of papers. General transportation analysis was also preferred among researchers, accounting for 31.25% of the database. On the contrary, rail transportation, air transportation and maritime transportation only had a small portion. It was mainly due to the high utilization rate of road transportation and its resulting transportation issues.

Although compared to road transportation, the number of publications focusing on maritime transportation was relatively small, and even experienced a slight decrease from ‘2006-2011’ period to ‘2012-2017’ period, maritime transportation has the potential to attract more attention in the future.

	Oil and gas	Main bulk commodities (iron ore, coal, grain, bauxite and alumina and phosphate rock)	Dry cargo other than main bulk commodities	Total (all cargo)
1970	1 440	448	717	2 605
1980	1 871	608	1 225	3 704
1990	1 755	988	1 265	4 008
2000	2 163	1 295	2 526	5 984
2005	2 422	1 709	2 978	7 109
2006	2 698	1 814	3 188	7 700
2007	2 747	1 953	3 334	8 034
2008	2 742	2 065	3 422	8 229
2009	2 642	2 085	3 131	7 858
2010	2 772	2 335	3 302	8 409
2011	2 794	2 486	3 505	8 785
2012	2 841	2 742	3 614	9 197
2013	2 829	2 923	3 762	9 514
2014	2 825	2 985	4 033	9 843
2015	2 947	2 951	4 150	10 047

Figure 2.2 Developments in international seaborne trade, selected years (Millions of tons loaded)

(Sources: UNCTAD 2016 REVIEW OF MARITIME TRANSPORT)

According to Figure 2.2, the world maritime transportation volumes maintained a high growth rate over the past decades, and even exceeded 10 billion tons in 2015. However, the unprecedented growing rate of maritime transportation on one hand contributes to industrial prosperity, but on the other hand renders many problems, like optimal ship route selection, cost/profit optimization, maritime safety/security and risk assessment. As game theory is effective against these problems, more researchers in this field will begin to apply game theory into maritime transportation in the future.

2.7 SUMMARY

From the reviewed literature, several conclusions can be made:

1) When applied in risk-based PSC inspection study, according to the reviewed literature, BN shows its superiority (e.g. bi-directional analysis) over risk assessment approaches, presenting a novel way to analyse PSC inspections for ship owners and port authorities. In other words, whenever the information about a specific ship concerning the defined nodes is obtained, its ship owner/operator or the authority of the port that the ship visits can use the BN based PSC model to analyse the detention probability of the ship in a forward risk prediction. If the ship is detained, the owner/operator can use it again to analyse the most probable causes leading to the detention in a backward risk diagnosis. Furthermore, it combines the visualized graph with mathematical knowledge, enabling it to analyse the inner relationship between

different variables influencing PSC inspection results. However, because of the research challenges on CPTs and network construction, BN's advantages in risk-based PSC have not yet been appropriately explored, revealing the major research gap to be fulfilled.

2) The nature of PSC inspection is a strategic problem between different stakeholders (e.g. port authority and ship owner), and the inspection policies demand to be settled properly and optimally. Game theory, as a mathematical tool to study the conflicts and cooperation between decision-makers, is validated by historical research on transportation, whether road or marine transport. Meanwhile, because of the scarcity of related papers on this academic field, game theory is a proper method to analyse the relationship between different stakeholders in PSC inspection.

In addition, the implementation of NIR in 2011brought PSC inspection to a new level, as stated by the chair and many senior executives of the Paris MoU. On this occasion, the optimal inspection policies and the decision-making framework for port authorities need to be clarified. However, none of the publications focuses on this topic.

3) Due to the implementation of NIR, company performance becomes a key influencing variable and indeed needs to be considered as a major risk factor in the decision-making process of PSC inspections, revealing a new research gap to be filled.

4) When searching the literature from various sources (e.g. Web of Science, Google Scholar), there is no research related to the implementation of NIR in PSC inspection or the analysis of the impact of the implementation of NIR on PSC inspection. Since the Paris MoU propagated that the introduction of NIR is the most important change in PSC history, it is necessary to figure out whether the implementation of NIR brings positive and significant changes to the PSC inspection system.

CHAPTER 3 REALISING ADVANCED RISK-BASED PORT STATE CONTROL INSPECTION USING DATA-DRIVEN BAYESIAN NETWORK

In this chapter, a data-driven Bayesian Network (BN) based approach is proposed to analyse risk factors influencing PSC inspections, and predict the probability of vessel detention. To do so, inspection data of bulk carriers in several major European countries in the Paris MoU is collected to identify the relevant risk factors, and categorised into two groups: '2005-2008' (corresponding to the period before NIR implementation) and '2015-2017' (corresponding to the period after NIR implementation). Meanwhile, the network structure is constructed via Tree Augmented Naive (TAN) learning and subsequently validated by sensitivity analysis. The model exploits a novel way to predict the detention probabilities under different situations, which effectively help port authorities to rationalise their inspection regulations as well as allocation of their resources.

3.1 INTRODUCTION

The past decades witnessed an unprecedented growing rate of maritime transportation demand, which on one hand contributes to industrial prosperity, but on the other hand renders threats and risks to the maritime industry, including but not limited to, ship collisions, stranding, fire, and oil spill causing large property losses, environmental pollution and casualties. For instance, the grounding of the Exxon Valdez, the capsizing of the Herald of Free Enterprise and the Estonia passenger ferry are well-known accidents in maritime transportation. These accidents attracted the attention of the world on maritime safety (Yang, et al., 2013; Yang, et al., 2014; Li, et al., 2014) and Port State Control (PSC) inspections have been implemented as an administrative measure to reduce the occurrence of maritime accidents and ensure maritime safety (Viladrich-Grau, 2003; Li & Zheng, 2008).

PSC inspections, which render port authorities the ability to inspect vessels in their own ports, are set up in order to prevent illegal actions of ship owners and maritime accidents. The PSC officers select high-risk vessels for inspection according to the risk estimation mechanism suggested by the regional PSC organizations (Xu, et al., 2007). If a vessel fails to pass the inspection, it will face a certain level of detention based on its safety status. Actually, PSC inspections are regarded as the last line of defence in coping with substandard vessels that may cause maritime accidents. It is however well noted that although risk analysis approaches, qualitative or quantitative, have been widely used to enhance maritime safety in recent years, they have been insufficiently utilized in the PSC inspection area in the literature.

This chapter aims to develop the risk assessment models using Bayesian Networks (BNs) to reveal the degree of importance of different risk factors influencing PSC inspection results, as well as predict the detention rate of individual vessels under different situations. Because of the implementation of NIR in 2011, the PSC inspection conditions before and after the NIR are different, indicating two BN models are needed, one for each period, respectively. In order to build the models, the bulk carrier data of some major European countries from 2005 to 2008 and 2015 to 2017 has been collected from the Paris MoU online inspection database (www.parismou.org/inspection-search). Meanwhile, the causal factors related to PSC inspections are also identified from this database. Due to the implementation of NIR and database system update, the factors identified from two periods are slightly different, which is illustrated in detail in a later section. The dependency among these factors and the causal relationships between them are simulated using a qualitative diagram in BN while the quantitative configuration of such dependency (i.e. conditional probabilities) is obtained using a gradient descent approach based on the collected dataset (Jensen, 1999). In fact, the BNs induced from the data-driven approach can reduce the disturbance of experts' judgements on the accuracy of the model results.

3.2 METHODOLOGY-THE CONSTRUCTION OF DATA-DRIVEN BN

Normally, the process of developing a data based BN model consists of four phases: data acquisition, BN structure learning, BN monitoring and analysis, and model validation (Zhang, et al., 2013). When applying it in the context of risk-based PSC inspections, a new conceptual methodology to analyse PSC inspections is developed including the following six steps in this study.

3.2.1 Data acquisition

To determine if a vessel is more likely to be detained, a list of historical PSC inspection records is necessary. The data used in this study is derived from the Paris MoU online inspection database (www.parismou.org/inspection-search, 2005-2008 and 2015-2017), which presents the details of inspections and provides a comprehensive and support dataset for this study.

There are two reasons for collecting the inspection records of these two periods: First, during the process of collecting data before the implementation of NIR, the Paris MoU online inspection database updated to a new system. In the new system, some information and risk factors existing in the old system were missing, i.e. dead weight tonnage and recognised organisation. Hence, in order to maintain consistency, only the data in 2005-2008 were collected. Second, the initial plan for the research project was to collect all the data after the implementation of NIR. However, because of the heavy workload on data collection work, only part of the data could be collected currently. Although compared to '2011-2014', '2015-2017' was a worse period according to the statistics provided by Paris MoU, it could provide us with more valuable information about the risks and uncertainties of PSC inspections under NIR, as worst cases are always given high priority in risk assessment.

Figure 3.1 and Figure 3.2 illustrate the interface of the Paris MoU inspection database and an example of one Paris MoU online inspection report.

	IMO	Name	Flag	Type	Age	Date of Inspection	Type of inspection	Port of inspection	Number of Deficiencies	Result
Details	9306627	KUDOS	Marshall Islands	Oil tanker	11	01/01/2018	More detailed inspection	Croatia - Omisalj	0	
Details	9389227	LADY GIOVI	Panama	Bulk carrier	11	01/01/2018	More detailed inspection	United Kingdom - Teesport	1	
Details	8716100	POLARIS VG	Finland	Ro-Ro cargo	29	01/01/2018	More detailed inspection	Germany - Rostock	0	
Details	9137193	SMN EXPLORER	Liberia	General cargo/multipurpose	23	01/01/2018	More detailed inspection	Sweden - Varberg	2	
Details	9506253	ULUSOY-14	Turkey	Ro-Ro cargo	6	01/01/2018	More detailed inspection	Italy - Trieste	0	
Details	9186405	A2B INDEPENDENT	Netherlands	Container	20	31/12/2017	Initial inspection	United Kingdom - Immingham	7	
Details	9716016	BW BORON	Isle of Man, UK	Chemical tanker	2	31/12/2017	More detailed inspection	France - Marseille (GPM)	0	
Details	9718923	CAMINERO	Russian Federation	Chemical tanker	4	31/12/2017	More detailed inspection	Romania - Constanta	0	
Details	9147605	EIJA	Finland	General cargo/multipurpose	22	31/12/2017	Initial inspection	Estonia - Paljassaare	3	
Details	8015881	FREYA	Russian Federation	Oil tanker	36	31/12/2017	Expanded inspection	Estonia - Paljassaare	4	
Details	8915627	FRI WAVE	Bahamas	General cargo/multipurpose	28	31/12/2017	More detailed inspection	Russian Federation - Vyborg	0	
Details	9479711	LIKYA C	Malta	Chemical tanker	10	31/12/2017	Initial inspection	Lithuania - Klaipeda	0	
Details	9463035	MAERSK EUBANK	Liberia	Container	7	31/12/2017	Initial inspection	Croatia - Rijeka	0	
Details	9235892	MASTERA	Finland	Oil tanker	16	31/12/2017	More detailed inspection	Russian Federation - Primorsk	10	Detention
Details	9110389	MSC KATYAYNI	Panama	Container	21	31/12/2017	More detailed inspection	Greece - Piraeus	1	
Details	9173692	TALI	Finland	General cargo/multipurpose	20	31/12/2017	More detailed inspection	Russian Federation - Vysotsk	0	

Figure 3.1 Paris MoU inspection search interface

(Source: Paris MoU)

Public Inspection

Ship Details

IMO Number	9465801	Name	AMALFI	Flag	Malta
Type	Bulk carrier	Gross Tonnage (GT)	40264	Keel Laying Date	25/6/2009
Age	9				

ISM Company

IMO Number	5529167	Address		Country	Greece
Name	TMS Dry Ltd	City			

Class Certificates

Class Certificate	Issue Date	Expiry Date
ABS	4/1/2015	17/11/2019

Statutory Certificates

Statutory Certificate	Issuing Authority	Issue Date	Expiry Date	Surveying Authority	Last Survey Date	Last Survey Place
International Sewage Pollution Prevention	ABS	13/11/2014	17/11/2019			
Cargo Ship Safety Radio	ABS	8/1/2018	17/11/2019			
International Ballast Water Management	ABS	8/1/2018	14/1/2022			
International Energy Efficiency Certificate	ABS	29/11/2015				
International Oil Pollution Prevention (IOPP)	ABS	15/1/2017	14/1/2022	ABS	8/1/2018	Korea, Republic of
Cargo Ship Safety Equipment	ABS	17/7/2017	17/11/2019	ABS	8/1/2018	Korea, Republic of
International Air Pollution Prevention	ABS	29/11/2015	17/11/2019	ABS	8/1/2018	Korea, Republic of
Cargo Ship Safety Construction	ABS	4/1/2015	17/11/2019	ABS	8/1/2018	Korea, Republic of
Load Line	ABS	4/1/2015	17/11/2019	ABS	8/1/2018	Korea, Republic of
Document of Compliance Dangerous Goods	ABS	29/11/2015	17/11/2019	ABS	8/1/2018	Korea, Republic of
International Ship Security	DNVGL	17/11/2016	29/1/2021			
Safety Management Certificate	DNVGL	17/11/2016	29/1/2021			
Maritime Labour Certificate	DNVGL	14/4/2018	10/7/2023			
Document of Compliance	DNVGL	2/1/2017	12/12/2021	DNVGL	23/3/2018	Greece
Tonnage	Malta	24/12/2013				
Continuous Synopsis Record	Malta	18/11/2016				

Figure 3.2 An example of PSC inspection online report

(Source: Paris MoU)

3.2.2 Variable identification

Based on the inspection records from the Paris MoU database, the variables of different periods are identified. Because of the heavy workload to collect inspection records manually from the Paris MoU inspection database[1], it is impossible for us identify all the factors and information presented in inspection records (Figure 4.2). Hence, only the factors shown at the interface and some important factors in inspection reports are counted, including:

[1] The Paris MoU inspection related data can only be viewed online, but not downloaded since it has been restricted by the Paris MoU Committee. Hence, the data in this study is collected manually or with the help of web crawler software.

1) 2005-2008: vessel flag, Recognized Organization (RO), dead weight tonnage (DWT), vessel age, type of inspection, port of inspection and number of deficiencies.

2) 2015-2017: vessel flag, vessel age, company performance, type of inspection, port of inspection, date of inspection, number of deficiencies

It is noteworthy that the factors concerned are those influencing detention, rather than inspections. In this study, the risk variables are set as the 'root variables', or 'first level risk variables' influencing detention rates of vessels. The inspection result 'Detention' is the target node. However, the size of the relevant CPT table would have been enormous if all root variables are defined as the parent nodes of inspection results in terms of 'detention'.

To solve this issue, two intermediate level risk variables are introduced based on the principle of divorcing approach (Jensen, 2001), one is 'vessel group', and the other is 'inspection group'. Vessel-related root variables (i.e. vessel age, flag, RO, DWT) and inspection-related root variables (i.e. type of inspection, port of inspection, and number of deficiencies) are connected as the parent node of the two intermediate level variables, respectively. Then the two intermediate level risk variables will act as the parents of the node 'detention'. In fact, they are two dummy variables to help reduce CPT calculation work. 'Vessel group' is the child node of vessel-related variables, while 'Inspection group' is the child node of inspection-related variables. They are at the same level in the network and jointly act as the parent nodes of 'Detention'. The hierarchical BN structure can significantly reduce the CPT calculation work (Huang, et al., 2006).

The detailed information and idea evolution of solving this issue will be presented in section 4.3.

3.2.3 Structure learning through data-driven approach

After identifying risk variables in the second step, a qualitative BN representing their interactive dependencies can be constructed through a data-driven approach, called Tree Augmented Naive (TAN) learning (Friedman, et al., 1997; Carvalho, et al., 2007).

3.2.3.1 Naïve BN (NBN)

In data analysis and pattern recognition, a classifier is a function that assigns a class label to evidence described by a set of attributes. As one of the most effective classifiers, naïve

Bayesian classifier is popular among the classifiers because of its predictive performance. The classifier learns from training data to compute the conditional probability of each attribute variable A_i given the class label C. Based on the assumption that all the attributes are conditionally independent given the value of C, the probability of C given the particular evidence can be calculated through Bayes rules. According to the value, the evidence is classified into a certain state of the class label.

When presented as a Bayesian network, the naïve BN is described as follows in Figure 3.3.

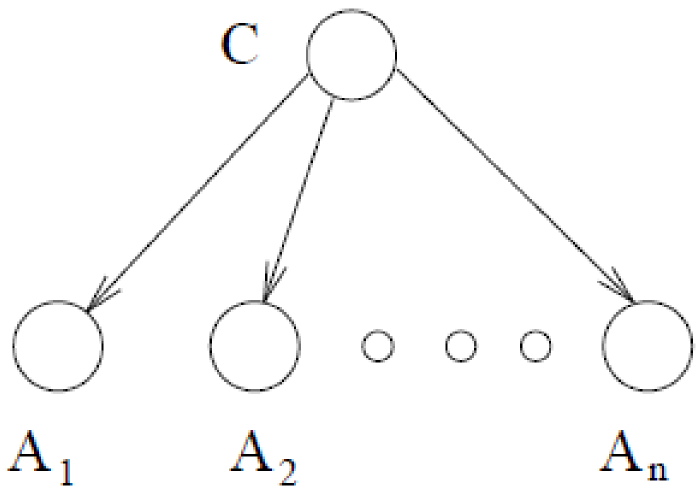

Figure 3.3 An example of naïve BN

(Source: Bayesian Network Classifiers, 1997)

The naïve BN was named by Titterington et al. (1981). It is a network where each target node is independent from other nodes and the target node is connected with all other nodes. The target node has no parents in this type of model. Although the assumption of NBN is unrealistic because the correlations among the factors exists in most problems, it is a still basic network of many other derived approaches and their networks, i.e. augmented naive BN and tree augmented naïve BN. Sun & Shenoy (2007) applied NBN to predict the bankruptcy, as well as help related stakeholders to make business decisions.

3.2.3.2 TAN learning

In order to improve the performance of NBN to comply with the reality, the NBN structure is augmented with links among the attributes or factors. This kind of structure that does not require independence among attributes is called augmented naïve BN (ABN). Further, if the class variable has no parents and each attribute has the class variable and at most one other attribute as parents, the ABN under this condition is called tree-augmented naïve (TAN) BN. The process of learning and constructing TAN model is named TAN learning.

The essence of TAN learning is actually an optimization problem. Let $A_1 \dots A_n$ be the attribute variables (e.g. the first level root variables) and C be the class variable (e.g. 'Vessel group') in PSC inspection. Π_C represents the parent variables of *C*. B is defined as a TAN model if $\Pi_C = \emptyset$ and there is a function π that defines a tree over $A_1, \dots, A_n$ such that $\Pi_{A_i} = \{C, A_{\pi(i)}\}$ if $\pi(i) > 0$, and $\Pi_{A_i} = \{C\}$ if $\pi(i) = 0$. The optimization problem consists on finding a tree defining function π over $A_1 \dots A_n$ such that the log likelihood is maximized, and the TAN model under this function is the structure of the target BN model. One difference between BN model and TAN model lies in class variables. Class variables in a normal BN model always have at least one parent node, meaning it is an intermediate-level variable, but in the TAN model it is the 'terminal' of the structure. Additionally, the TAN model is a diverging model, which is different from normal recognition of converging BN.

The procedure called Construct-TAN can solve this optimization problem. This procedure follows the general outline proposed by Chow and Liu (1968), except that instead of using the mutual information between two attributes, it uses conditional mutual information between attributes given the class variable. This function is defined as

$$I_P(\boldsymbol{A_i}; \boldsymbol{A_j} | \boldsymbol{C}) = \sum_{\boldsymbol{a_{ii}}, \boldsymbol{a_{ji}}, \boldsymbol{c_i}} P(\boldsymbol{a_{ii}}, \boldsymbol{a_{ji}}, \boldsymbol{c_i}) log \frac{P(\boldsymbol{a_{ii}}, \boldsymbol{a_{ji}} | \boldsymbol{c_i})}{P(\boldsymbol{a_{ii}} | \boldsymbol{c_i}) P(\boldsymbol{a_{ji}} | \boldsymbol{c_i})} \tag{3-1}$$

where I_P represents the conditional mutual information, $\boldsymbol{a_{ii}}$ is the *i*th state of attribute variable $\boldsymbol{A_i}$, $\boldsymbol{a_{ji}}$ is the *i*th state of attribute variable $\boldsymbol{A_j}$, $\boldsymbol{c_i}$ is the *i*th state of class variable $\boldsymbol{C_i}$.

This function measures the information that $\boldsymbol{A_i}$, $\boldsymbol{A_j}$ both have when the value of $\boldsymbol{C}$ is known.

The Construct-TAN procedure of PSC inspection consists of five main steps:

a) Compute $I_P(A_i, A_j | C)$ between each pair of attribute variables in PSC inspection, $i \neq j$.

Attribute variables in PSC inspection: vessel flag, Recognized Organization (RO), dead weight tonnage (DWT), vessel age, type of inspection, port of inspection and number of deficiencies.

Class variables in PSC inspection: vessel group, inspection group

b) Build a complete undirected graph in which the vertices are the attributes $A_1,\ldots, A_n$. Annotate the weight of an edge connecting A_i to A_j by $I_P(A_i, A_j \mid C)$.

c) Build a maximum weighted spanning tree.

Spanning tree: A spanning tree is a connected subgraph containing no cycles.

Maximum weighted spanning tree: The maximum weighted spanning tree is a spanning tree that has a larger sum of weights on its edges than any other spanning tree.

Therefore, the maximum weighted spanning tree in our study is the tree that has a maximum sum of $I_P(A_i, A_j \mid C)$.

d) Transform the resulting undirected tree to a directed one by choosing a root variable from the attribute variables and setting the direction of all edges to be outward from it.

e) Construct a TAN model by adding a vertex labelled by class variable *C* and adding an arc from *C* to each A_i.

Compared to other data-driven network construction approaches, like naive BN (Langley, et al., 1992) and C4.5 (Quinlan, 1995), TAN is proved to be more competitive and accurate (Murphy & Aha, 1995).

3.2.4 CPT distribution of the risk-based PSC BN

When the structure of the PSC BN is confirmed, the conditional probabilities of the nodes are required to model the uncertainties of risk variables. In this thesis, the CPTs are formulated by using a gradient descent approach (Jensen, 1999; Bottou, 2010).

In the developed PSC BN, there exists evidence *e*, for example, the inspection database from 2005-2008. For a particular variable *V*, take 'Vessel age' as an example, we have $\boldsymbol{x} = P(V \mid e) = (x_1, \ldots, x_n)$, which reflects the conditional probabilities of different states of 'Vessel age'. Meanwhile, we have a prior request $\boldsymbol{y} = (y_1, \ldots, y_n)$ for $P(V \mid e)$. If the structure of BN is determined, the conditional probabilities associated with 'vessel age' are described by a set $\boldsymbol{t} = (t_1, \dots, t_m)$, for example, $P(vessel\ group =' \ high\ detention\ risk' | V = 'morethan20')$. Set $\boldsymbol{t}$ has an initial value $\boldsymbol{t}_0$, which is based on the estimation or related experience. According to Bayes' rules, the conditional probability of 'vessel age' can be calculated as a function of set $\boldsymbol{t}$**,** denoted as $\boldsymbol{x} = P(V \mid e) = F(\boldsymbol{t})$. The objective of gradient descent approach is to adjust the conditional probability set $\boldsymbol{t}$ so that $P(V \mid e)$ is sufficiently close to $\boldsymbol{y}$**.** Once this objective is satisfied, the value of set ***t*** at this time is the corresponding conditional probabilities in the BN model of PSC.

A distance measure approach is introduced, called *Euclidean* distance ($dist_E$):

$$dist_E(\boldsymbol{x}, \boldsymbol{y}) = \sum_i (x_i - y_i)^2 \tag{3-2}$$

It is a metric, having the following characteristics:

1. $dist_E(\boldsymbol{x}, \boldsymbol{y}) = 0$ if and only if **x** = **y**
2. $dist_E(\boldsymbol{x}, \boldsymbol{y}) \leq dist_E(\boldsymbol{x}, \boldsymbol{z}) + dist_E(\boldsymbol{z}, \boldsymbol{y})$
3. $dist_E(\boldsymbol{x}, \boldsymbol{y}) = dist_E(\boldsymbol{y}, \boldsymbol{x})$

The task is to set the conditional probability set $\boldsymbol{t}$ such that the distance is as small as possible. If it is possible to determine $dist_E(\boldsymbol{x}, \boldsymbol{y})$ as a function of ***t***, then the problem can be solved directly. However, usually the problem cannot be solved directly even when the function is known, and a gradient descent method can be used:

a) Calculate **grad** $dist_E(\boldsymbol{x}, \boldsymbol{y})$ with respect to set ***t***.

b) Give $\boldsymbol{t}_0$ a displacement $\Delta \boldsymbol{t}$ in the direction opposite to the direction of the **grad** $dist_E(\boldsymbol{x}, \boldsymbol{y})(\boldsymbol{t}_0)$, which is denoted as:

$$\Delta \boldsymbol{t} = -\alpha\ \mathbf{grad}\ dist_E(\boldsymbol{x}, \boldsymbol{y})(\boldsymbol{t}_0)$$

Where the step size $\alpha > 0$.

c) Iterate this procedure until the gradient is close to 0.

From the definition above, the following is obtained:

$$\mathbf{grad}\ dist_E(\boldsymbol{x},\boldsymbol{y})(\boldsymbol{t}) = \sum_i 2(x_i - y_i)\mathbf{grad}\boldsymbol{x_i}(\boldsymbol{t}) \tag{3-3}$$

Once the adjustment process stops, the latest values of set ***t*** are defined as the conditional probabilities in BN model of PSC.

3.2.5 Generation of posterior probabilities and risk prediction

Once the BN structure and CPTs are properly constructed, the unobservable situations associated with PSC inspection can be predicted through the generated posterior probabilities when observable evidence is provided. Bayes' rule is applied to obtain the posterior probabilities in this study illustrated as follows:

Imagine there are only two variables 'vessel age' and 'vessel group', and 'vessel age' is the parent node of 'vessel group'. Set 'vessel age' as M, 'vessel group' as N, '$M = M_i$' means the vessel is at its *i*th 'vessel age' state and the same goes to '$N = N_j$'.

According to Bayes' rule, the joint probability

$$P(M = M_i, N = N_j) = P(M = M_i) \times P(N = N_j | M = M_i)$$

Where: $P(M = M_i, N = N_j)$ represents the joint probability that events '$M = M_i$' and '$N = N_j$' both occur, $P(M = M_i)$ denotes the prior probability of the *i*th 'vessel age' state, $P(N = N_j | M = M_i)$ denotes the conditional probability of the occurrence of *i*th 'vessel age' state given that *j*th 'vessel group' state occurs.

If the state of 'vessel group' is locked and the state of 'vessel age' is changed to different states, the sum of joint probabilities is known as the probability of *i*th 'vessel group' state described as follows:

$$P(N = N_j) = \sum_i P(M = M_i) \times P(N = N_j | M = M_i) \tag{3-4}$$

Further, when the variable *N* has more than one parent node, the probability of *i*th 'vessel group' state can also be calculated through Equation (3-4) as it is a special case of binary variables.

Imagine $M^0, M^1, M^2, \dots, M^n$ are parent nodes of N, and the ith state of kth parent nodes are represented as '$M^k = M^k_{i(k)}$' . Through applying Equation (3-4), the probability of jth 'vessel group' state described as follows:

$$P(N = N_j) = \sum_{i(k)} P\left(M^1 = M^1_{i(1)}, M^2 = M^2_{i(2)}, \dots, M^k = M^k_{i(k)}\right) \times P\left(N = N_j | M^1 = M^1_{i(1)}, M^2 = M^2_{i(2)}, \dots, M^k = M^k_{i(k)}\right)$$

Where *i (k)*, *k*= 1, 2... n, are independent numbers.

3.2.6 Sensitivity analysis

Sensitivity analysis is known as a way to determine how the uncertainty in the output of a model can be influenced by the different sources of uncertainty in its input. In this particular study, a two-step sensitivity analysis has been developed to not only determine the influence degree of risk variables, but also validate the proposed model.

3.2.6.1 Mutual information calculation

Entropy is described as a value that, when increased, can be interpreted as increase in uncertainty of a dataset which would then require more information in order to describe that data. Consider a discrete random variable $\boldsymbol{\alpha}$ with possible values $\{\alpha_1, \alpha_2, \dots, \alpha_i\}$ and probability mass function $P(\boldsymbol{\alpha})$, then the entropy can be explicitly written as:

$$H(\boldsymbol{\alpha}) = -\sum_i P(\alpha_i) log_b P(\alpha_i)$$

Where b is the base of the logarithm used. Normally, the value of b is 2.

Based on entropy theory, mutual information (entropy reduction) is introduced in this research to measure the mutual dependence of different variables, or in other words, it is the information that two variables share. It is the value used to calculate the strengths of the relationships between the target node (i.e. detention) and influencing nodes (i.e. vessel age, vessel flag). One of the advantages of mutual information is that it can be computed between variables at different layers. When a new observation of an influencing variable is obtained, the mutual information can help measure the uncertainty of the observation on target node.

Since our objective is to find the relationship between risk variables and ‘detention’, ‘detention’ is chosen as a fixed variable in mutual information calculation. Therefore, the mutual information between ‘detention’ and other risk variables can be defined as:

$$I(D,\beta) = -\sum_{d,i} P(d,\beta_i) log_b \frac{P(d,\beta_i)}{P(d)P(\beta_i)} \tag{3-5}$$

Where D represents ‘detention’, β represents risk variable, β_i represents the *i*th state of β, $I(D,\beta)$ represents the mutual information between ‘detention’ and risk variables. The value of $I(D,\beta)$ is only related to the two variables D and β, and it is independent to other mutual information in the model. The larger the value of mutual information, the stronger relationship which exists between variable ‘β’ and ‘detention’.

It is noteworthy that the amount of mutual information represents the degree of influence, not the exact influence of variables. The application of mutual information in this thesis is to clarify the strength of the relationships between influencing factors and ‘detention’. The factors having stronger relationships with ‘detention’ are viewed as significant variables and will be selected to test their influence through scenario simulation in section 3.2.6.2.

3.2.6.2 Scenario simulation - the effects of different variables

Once the variables are selected from mutual information calculation, scenario simulation, another form of sensitivity analysis, is needed to determine the influence of these variables. The classical way to set a scenario is to lock all the other nodes and change the target node gradually, for example, 10% as a step for up and down, and the changes rate can be used to analyse the effect of this variable. However, this approach has an obvious drawback that it is only suitable for variables having two states. For those who have more than two states, the classical way is not workable. Take the variable ‘vessel age’ in this study as an example, it has five states ‘0 to 5 years’, ‘5 to10 years’, ’10 to15 years’, ’15 to 20 years’ and ‘over 20 years’ (the reason for the classification is in section 4). If we increase the state ‘over 20 years’ from 0% to 10%, the overall value of other states will decrease from 100% to 90% accordingly. Actually, the combinations in this case are innumerable, and it is impossible to decide which one should be applied. Therefore, the traditional scenario simulation (sensitivity analysis) is inappropriate to our study.

To overcome the difficulties, a new method (Alyami, et al., 2016) is applied in this study. The method has been applied to the container port risk analysis to test the impact of hazardous events on container port system. The results of empirical study and experiments carried out by Alyami proved the method to be reasonable and reliable. Hence, it is selected in this research project. First, increase the probability of the state that can generate the highest detention rate to 100% to obtain the High Risk Inference (HRI). Secondly, increase the probability of the state that can generate the lowest detention rate to 100% to obtain the Low Risk Inference (LRI). Finally, the average value of HRI and LRI will show the True Risk Influence (TRI) of each risk variable in the entire PSC inspection system, and it is described as follows:

$$TRI = \frac{\text{HRI} + \text{LRI}}{2} \tag{3-6}$$

The sensitivity analysis results, or in other words, the influence degree on 'detention' of different risk variables, can therefore be ranked according to the value of TRI.

Through this approach, the downside of classical scenario simulation (sensitivity analysis) can be overcome.

In general, the sensitivity analysis in this thesis is consist of two parts: the mutual information analysis to test the strength of relationships and select the significant variables, the scenario simulation part to present the exact influence of these variables.

3.2.7 Model validation

If the methodology and method in our study is reasonable and logical, then the sensitivity analysis must at least satisfy the following two axioms (Yang, et al., 2009; Jones, et al., 2010; Li, et al., 2014):

Axiom 1. A slight increase/decrease in the prior 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* attributes (sub-evidence), where *y* is a subset of *x*, *x-y* refers to the attributes from *x* and not belong to *y*

3.3 BN MODEL FOR PSC INSPECTION BEFORE THE IMPLEMENTATION OF NIR IN 2008 – 'PRE-NIR BN MODEL'

3.3.1 Data

A database containing 72,785 inspection records of different vessel types (e.g. bulk carrier, oil tanker, passenger vessel) before the implementation of NIR from 2005 to 2008 is established and named as 'Pre-NIR' database. To simplify the model, the model will focus on one specific vessel type.

As one of the most used vessel types currently, bulk carriers make up 15% - 17% of the world's merchant fleets and range in size from single-hold mini-bulk carriers to mammoth ore ships able to carry 400,000 metric tons of deadweight (DWT). Such phenomena and trends can also be found in PSC inspection records. 11,366 inspections related to bulk carriers are recorded in the Paris MoU system, making up 15.62% of the total number of PSC inspections. Hence, as one of the important maritime carriers, the bulk carrier is selected as the research target in this study.

3.3.2 Risk variables

The risk variables identified from inspection records are explained with a particular reference to their state definitions as follows:

(1) Vessel flag

Each year a new White, Grey and Black list is published in the Paris MoU Annual Report (ParisMoU, 2005-2017). The "White, Grey and Black (WGB) list" presents the full spectrum, from quality flags to flags with a poor performance that are considered to have a high or very high risk. It is based on the total number of inspections and detentions over a 3-year rolling period for flags with at least 30 inspections.

This variable has four states: 'White', 'Grey', 'Black' and 'Black (high risk)', where the performance of each state decreases successively.

(2) Recognized Organization (RO)

The performance of recognized organizations is also summarized into a performance list by the Paris MoU. According to Recognised Organisation Performance table published by the Paris MoU every year, only those ROs that had 60 or more inspections in a 3-year period are taken into account.

Meanwhile, the RO table provides an official performance level classification: ‘high’, ‘medium’, ‘low’ and ‘very low’.

(3) Dead Weight Tonnage (DWT)

DWT is a measure of a vessel's weight carrying capacity, and does not include the weight of the ship itself. The ‘Review of maritime transport’ of United Nations Conference on Trade and Development (UNCTAD) (UNCTAD, 2016) classified bulk carriers into five categories according to DWT: ‘Small’, ‘Handysize’, ‘Handymax’, ‘Panamax’ and ‘Capesize’.

Dry bulk and ore carriers	
Capesize bulk carrier	100,000 dwt plus
Panamax bulk carrier	65,000–99,999 dwt
Handymax bulk carrier	40,000–64,999 dwt
Handysize bulk carrier	10,000–39,999 dwt

Figure 3.4 Bulk carrier categories

(Source: UNCTAD Review of Maritime Transport, 2016)

(4) Vessel age

Vessel age is another important factor influencing inspection results. Old vessels are more likely to suffer detention. In UNCTAD reports, vessel age is categorized in Figure 3.5.

		Years					Average age		Percentage change, 2015–2016
		0–4	5–9	10–14	15–19	20+	2015	2016	
World									
Bulk carriers	Percentage of total ships	42.83	25.46	11.97	9.86	9.89	9.04	8.83	-0.21
	Percentage of dead-weight tonnage	46.40	25.95	11.48	8.14	8.04	8.06	7.95	-0.11
	Average vessel size (dwt)	78 988	74 330	69 988	60 182	59 281			

Figure 3.5 Age distribution of bulk carriers 2016

(Source: UNCTAD Review of Maritime Transport 2016)

Refer to this table, vessel age has 5 states of ‘0 to 5 years’, ‘5 to10 years’, ’10 to15 years’, ’15 to 20 years’ and ‘over 20 years’, where ‘0 to 5 years’ means $0 \leq x < 5$, and so as others.

(5) Type of inspection

A PSC officer visiting a ship will conduct a general inspection of several areas to verify that the overall condition of the ship complies with the requirements of PSC.

If the ship is in full compliance, the PSC Officer will issue a ‘clean’ inspection report (Form A) to the master of the ship. In the case that any deficiency is identified, the inspection report will include a deficiency-found report (Form B) indicating any follow-up actions to be taken to rectify the deficiencies indicated. Furthermore, control on compliance with on-board operational requirements may be included in the control procedures, particularly if an officer has a reason to believe that the crew demonstrates insufficient proficiency in that area.

This variable therefore has the three states of ‘Initial inspection’, ‘More detailed inspection’ and ‘Expanded inspection’.

(6) Port of Inspection

The Paris MoU consists of 27 participating maritime administrations and covers the waters of the European Coastal States and the North Atlantic basin from North America to Europe.

Seven major countries investigated in the research are Belgium, France, Germany, Italy, Netherlands, Spain and UK, which occupy 6,913 cases in 11,000 inspection records.

(7) Number of deficiencies (No. of deficiencies)

During an inspection, a vessel may face detention if it is detected with deficiencies. There are different types of deficiencies, such as alarms, cargo operations, fire safety, navigation safety, ISPS. These deficiency types can be divided into two groups: major deficiencies and minor deficiencies. Major deficiencies can lead to direct detention regardless of its combination with other deficiencies.

From the inspection records, the detention rate increases dramatically between the following states: ‘0’, ‘1 to 3’, ‘4 to 9’ and ‘more than 10’ (the number of inspected deficiencies are integer, e.g. ‘0’ means 0 deficiency in inspection, ‘1 to 3’ means the number of deficiencies are 1, 2 or 3). Hence, these four states are applied to node ‘number of deficiencies’.

(8) Detention

In taking a decision concerning the rectification of a deficiency or detention of a ship, the PSC Officer (PSCO) will take into consideration the results of the more detailed or expanded inspection carried out in accordance with the Memorandum and the procedures mentioned in the Paris MoU committee instruction. The PSC officers will exercise professional judgment in determining whether to detain the ship until the deficiencies are rectified or to allow it to sail with certain deficiencies without unreasonable danger to the safety, health, or the environment, having regard to the particular circumstances of the intended voyage. As regards minimum manning standards and the provisions of the relevant ILO Conventions, special procedures will be observed.

If the deficiencies on a ship are sufficiently serious to merit a PSC officer returning to the ship to be satisfied that they have been rectified before the ship sails, then the vessel will be detained. In other words, if the deficiencies of the vessel are found to be the grounds for the detention, for example, 1) failure of proper operation of propulsion and other essential machinery; 2) absence, insufficient capacity or serious deterioration of personal lifesaving appliances, survival craft and launching arrangements, the vessel is viewed as a high risk vessel and has large probability to be detained.

The detention rates are expressed as a percentage of the number of inspections, rather than the number of individual ships inspected to take account of the fact that some ships are detained more than once a year.

This variable has two states, i.e. ‘Yes’ and ‘No’.

3.3.3 A new risk analysis BN model for PSC

The model for analysing PSC inspections is developed by considering the risk variables at different levels and their relationships mentioned in section 3.2. According to the TAN learning mentioned in section 3.2.3.2, ‘detention’ is selected as the target node (or class label) and the parent node of other root variables. However, the conditional mutual information calculation between each pair of child nodes, the determination of maximum weighted spanning tree, and the construction of directed network graph need to be achieved through other ways due to the complexity and impossibility to figure out these works manually.

Therefore, a BN software called Netica is applied in this research to help complete these works. Netica is a powerful, easy-to-use, complete program for working with belief networks and influence diagrams. It can help us to draw the network, and the relationship between risk variables. Further, it has several advanced techniques based on the fastest and most modern algorithms, for example, find the appropriate values or probabilities for some unknown variables, make use of influence diagrams to obtain the optimal decisions maximizing the expected values of the users' objectives, etc. Associated with this research, the function called 'Learn TAN Structure' can replace the manual calculation work of Equation (3-1) for BN structure construction. It provides a convenient way to avoid the heavy calculation work of learning TAN structure when the scale of structure is enormous.

In fact, during the process of constructing the BN in this research, several improvements were made on the original network until the optimal BN for PSC was found.

3.3.3.1 Original BN

Based on the inspection dataset of bulk carrier derived from the Paris MoU online database in 2005-2008, Figure 3.6 presents the original BN structure via TAN learning through Netica.

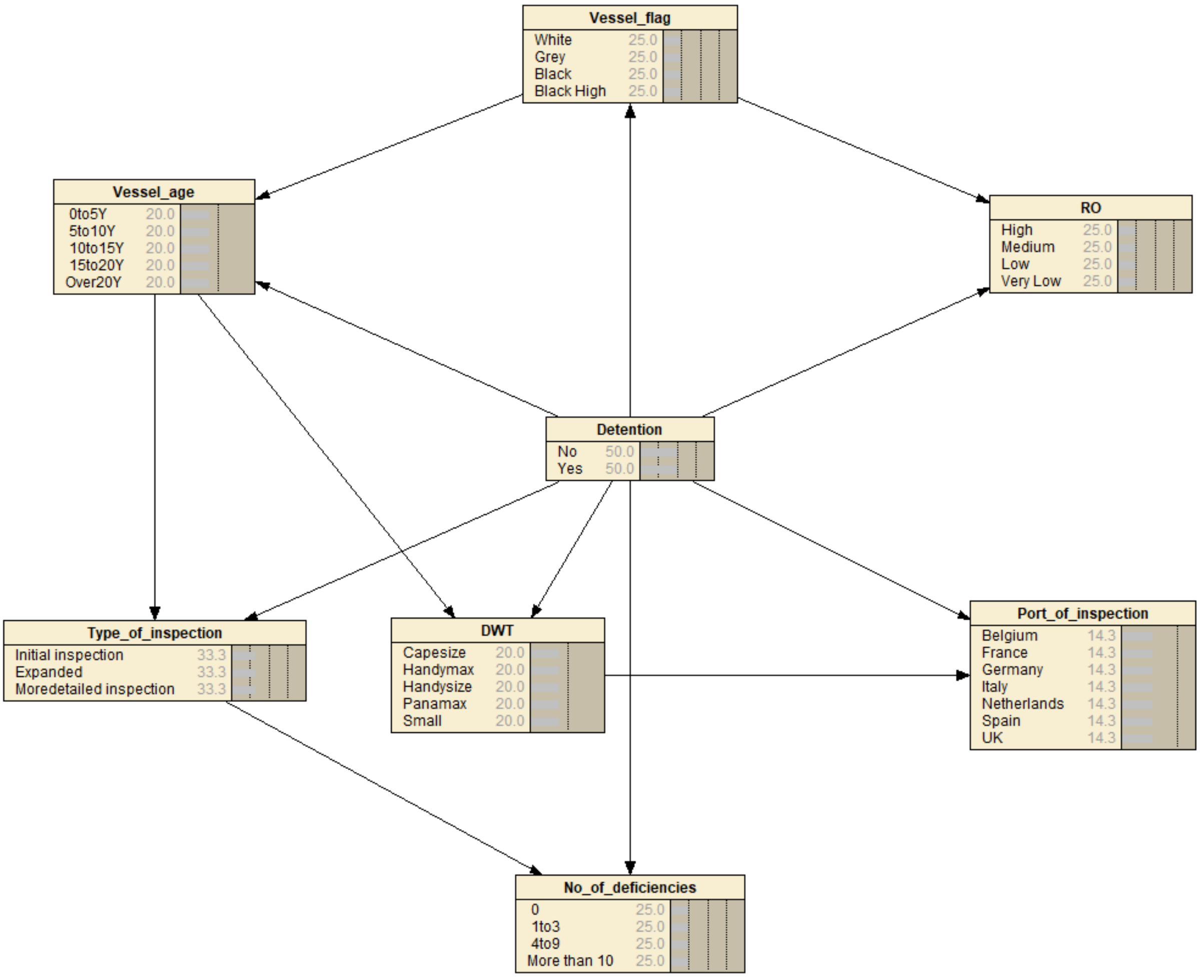

Figure 3.6 Original BN

(Source: Author)

In this structure, links between child nodes and 'detention' are 'leaving type', which makes the structure a diverging network. It is quite strange and different from normal BN because that the links usually start from the influencing nodes to the target node. The reason for Netica choosing 'diverging network' is that it attempts to avoid too many links entering each node which may cause the CPT tables to be too large to have enough sampling information to calculate.

There is no problem in having a great many links leaving a node, and since we will do Bayesian inference on the results, it is accepted for links to go in either direction. When classifying, predicting or diagnosing a particular variable with the best accuracy, it is required to have as many relationships with other variables as possible, resulting in many links leaving the variable. In other words, from a mathematical perspective, the diverging network is reasonable and it is a more appropriated structure type than 'converging type'.

In the original BN presented in Figure 3.6, apart from the target node ‘detention’, ‘vessel flag’, ‘vessel age’, ‘DWT’, ‘Type of inspection’ are the second-level variables that are not only the child nodes of ‘detention’, but also the parent nodes of other nodes. The rest of the nodes, ‘RO’, ‘Port of inspection’ and ‘Number of deficiencies’, are the nodes at the third-level that have no links pointing to other nodes. However, the relationships between risk factors revealed in this network still need to be verified and modified.

Deficiencies

1) Although the ‘diverging network’ is reasonable and proper from a mathematical perspective, it may be confusing for maritime practitioners that do not have the foundation of mathematics to see the links point from target factor to influencing factors. To make the model understandable and acceptable for all maritime practitioners, the network should conform to the basic logic that if factor A is influenced by factor B, then the link should point from B to A. By this logic, the links in the network should point from influencing factors (i.e. vessel age, inspection type) to the target factor ‘Detention’. Therefore, the network should be converted to ‘converging’ type, and the CPT calculation problems need to be solved under this situation.

2) Some links in the network are meaningless or even incorrect. For example, in the network, the ‘vessel age’ has an influence on ‘DWT’; however, it is a common sense that the two factors have no connection. There are still other similar cases or links in the mode. Therefore, the BN needs to be manually modified once it is created by Netica, aiming to eliminate unnecessary and false links.

3.3.3.2 Improved BN

In order to improve the network and overcome the deficiencies mentioned above, several changes are made to the original BN. The biggest challenge lies in the size of CPT and the calculation work on conditional probabilities when the network of the TAN model is changed to converging type.

The basic idea to handle this kind of problem is the principle of divorcing approach (Jensen, 2001). The essence of this approach is to split the parent nodes of target node into several sets. In this research, the set of parent nodes ‘vessel age’, ‘vessel flag’, ‘DWT’, ‘RO’ for ‘detention’ is divorced from the parent nodes ‘inspection type’, ‘port of inspection’, ‘number of deficiencies’ by introducing two mediating variables ‘vessel group’ and ‘inspection group’, making ‘vessel group’ the child of vessel-related variables and ‘inspection group’ the child of inspection-related variables. Both of them are parent nodes of ‘detention’.

➢ *Vessel group*

The variable ‘vessel group’, which presents the overall risk level of a vessel, is added to the network having connections with ‘detention’ and inspection-related variables. It has four parent variables, ‘vessel flag’, ‘DWT’, ‘vessel age’ and ‘RO’. Meanwhile, it is the parent node of ‘inspection type’ because port authorities will choose inspection types according to the type (i.e. high or low risk) of the inspected vessel.

Four parent nodes of ‘vessel group’ have a number of different combinations, and cases correlated with them can all be found in the PSC inspection database. If we select several cases with different combinations of vessel-related nodes and the same combination of inspection-related nodes, when inputting them into BN, the result reveals that most cases resulting in detention have a detention rate more than 10%, and other cases are lower than 10%.

(The selected combination of inspection-related nodes are under general conditions)

Therefore, in this study, this variable has two states of ‘High detention risk vessel’ and ‘Low detention risk vessel’.

➢ *Inspection group*

The ‘inspection group’ is set as the risk level of the inspection considering all inspection-related risk factors. Similar to ‘vessel group’, it also connects the inspection-related variables with ‘detention’. It has three parent variables, ‘type of inspection’, ‘port of inspection’ and ‘number of deficiencies’.

This variable has two states of ‘High detention risk’ and ‘Low detention risk’, and the distinguish criteria is also 10% detention rate as ‘Vessel group’.

Hence, the updated process of BN construction is illustrated as follows:

a) Divide the risk variables into two groups, ‘vessel group’ and ‘inspection group’

Vessel group

The first level variables are ‘vessel age’, ‘vessel flag’, ‘RO’, and ‘DWT’

The mediating level variable is ‘vessel group’.

Inspection group

The first level variables are ‘port of inspection’, ‘type of inspection’, and ‘number of deficiencies’.

The mediating level variable is inspection group.

b) The structure of each group is established via the TAN learning approach. ‘Vessel group’ and ‘Inspection group’ are set as the target node of each group respectively. Figure 3.7 and Figure 3.8 are the resulting structures of each group, respectively.

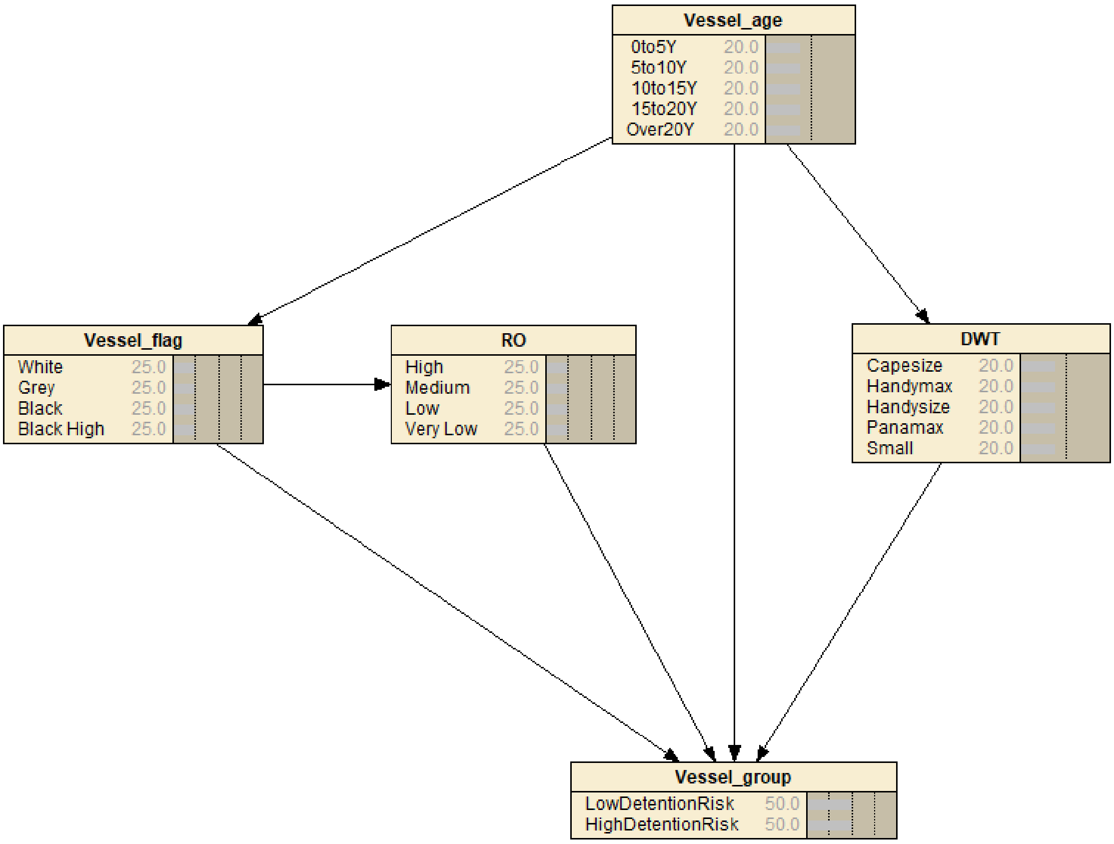

Figure 3.7 TAN structure of vessel group

(Source: Author)

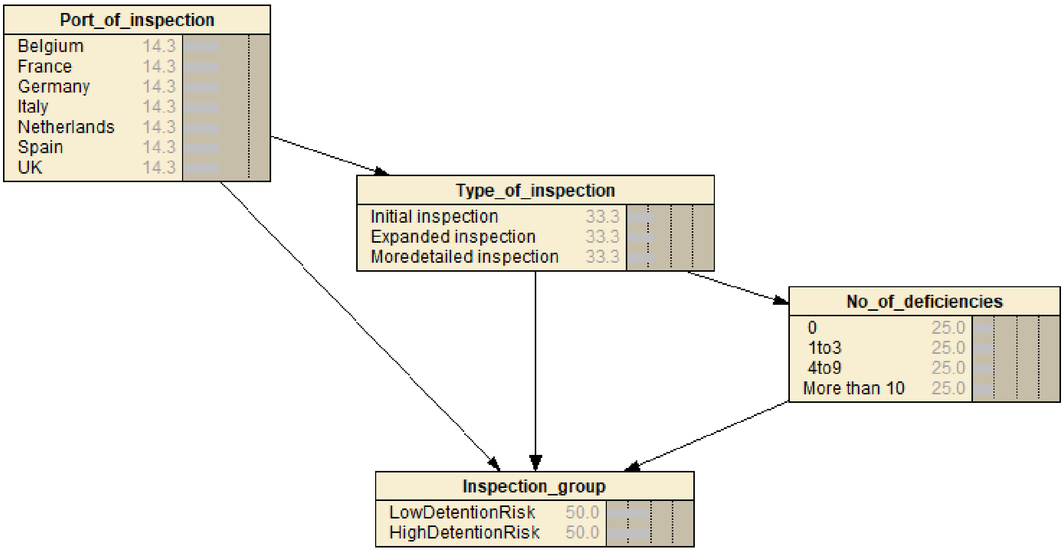

Figure 3.8 TAN structure of inspection group

(Source: Author)

c) Combine two group structures and ‘detention’ together to obtain the integrated BN structure, where ‘inspection group’ and ‘vessel group’ are parent nodes of ‘Detention’. The network is showed in Figure 3.9.

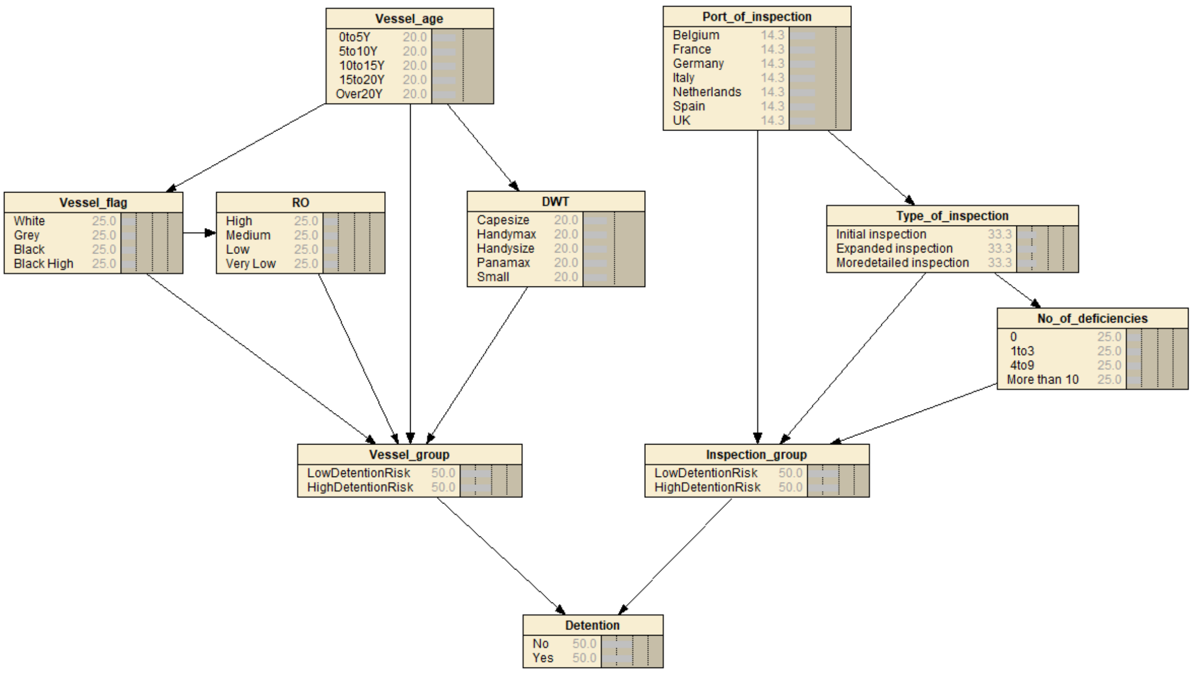

Figure 3.9 Improved BN

(Source: Author)

d) Amend the edges (or links) in the structure.

➢ As defined above, ‘Vessel group’ represents the risk level of the vessel. Before executing the PSC inspection, the PSCO will determine the inspection type according to the historical inspection records of this vessel and its risk level. Therefore, a link from ‘vessel group’ to ‘type of inspection’ is necessary.

➢ Some links should be eliminated because they are illogical and meaningless, including ‘vessel age-vessel flag’, ‘vessel age-dwt’, and ‘port of inspection-type of inspection’. These relationships do not conform to the real case.

e) The final structure of BN model for analysing PSC inspections is developed and presented in Figure 3.10.

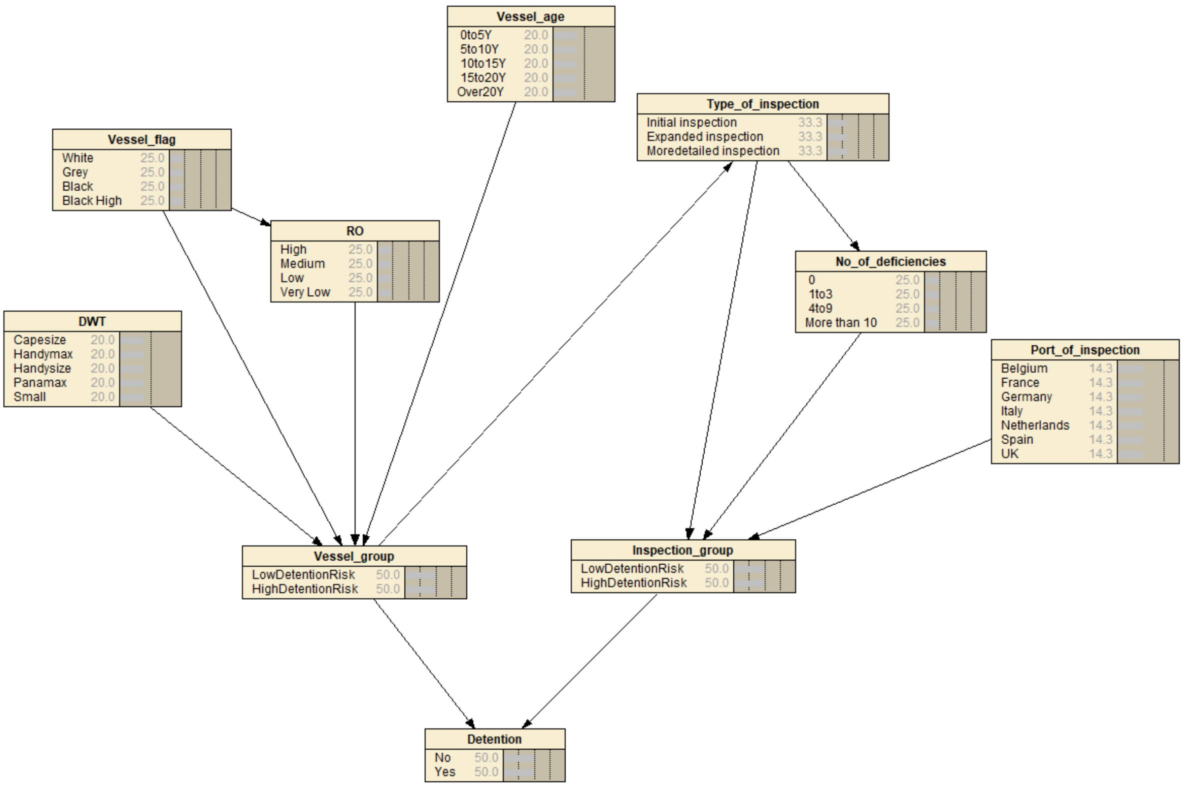

Figure 3.10 Proposed BN for PSC inspection

(Source: Author)

3.3.4 CPT and prior probabilities for each node

Once the model is developed, the next step is to establish the CPT table of each node. When executing the BN model, the conditional probabilities of each node will be calculated based on Equation (3-2) and Equation (3-3) mentioned in the gradient descent section.

Specifically, it is a three-step calculation process:

(1) With regard to the root nodes, the proportion of each defined state is used as the prior probabilities.

For instance, over the 6,913 inspection records, 926 vessels are 0-5 years old, 962 vessels are 5-10 years old, 1,050 vessels are 10-15 years old, 520 vessels are 15-20 years old, 3,455 vessels are over 20 years old. Therefore, the calculation provides the prior probabilities of vessel age as

0 - 5 years: 926/6913= 0.1340 **5 - 10 years**: 962/6913= 0.1392

10 - 15 years: 1050/6913= 0.1519 **15 - 20 years**: 520/6913= 0.0752

Over 20 years: 3455/6913= 0.4998

In a similar way, the prior probabilities of other root variables are presented in Table 3.1

Table 3.1 The prior probability of each root node

DWT						
Capesize	Handymax	Handysize	Panamax	Small		
0.0073	0.1284	0.5949	0.0094	0.2600		
Flag						
Black (High)	Black	Grey	White			
0.0103	0.2218	0.0671	0.7008			
Vessel age						
0to5Years	5to10Years	10to15Years	15to20Years	Over20Years		
0.1340	0.1392	0.1519	0.0752	0.4998		
Port of inspection						
Belgium	France	Germany	Italy	Netherlands	Spain	UK
0.1297	0.1360	0.0866	0.1564	0.1243	0.2356	0.1315

(Source: Author)

(2) Once prior probabilities of root variables are determined, they are served as the prior request for the subsequent gradient descent calculation for other first level and intermediate-level risk variables.

(3) Similar to step two, the conditional probabilities obtained in step 2 are set as the prior request for further calculation of third-level risk variable ‘detention’.

Tables 3.2 – 3.7 list the CPTs of ‘RO’, ‘type of inspection’, ‘number of deficiencies’, ‘detention’, and part of the ‘vessel group’ and ‘inspection group’. The full CPTs of ‘vessel group’ and ‘inspection group’ are too large to present here. Hence, they are placed in Appendix 1.

Table 3.2 CPT of RO

RO / Vessel flag	High	Low	Medium	Very Low
Black (High)	0.5819	0.2467	0.0565	0.1149
Black	0.9740	0.0044	0.0154	0.0063
Grey	0.8113	0.0316	0.0604	0.0967
White	0.9890	0.0036	0.0037	0.0036

(Source: Author)

Table 3.3 CPT of ‘type of inspection’

Type of inspection / Vessel group	Expanded Inspection	Initial Inspection	More detailed Inspection
Low Detention Risk	0.2769	0.3305	0.3926
High Detention Risk	0.5701	0.1021	0.3278

(Source: Author)

Table 3.4 CPT of ‘number of deficiencies’

No. of deficiencies / Type of inspection	4 to 10	More than 10	0 to 1	1 to 4
Expanded Inspection	0.3136	0.2079	0.2273	0.2512
Initial Inspection	0.1052	0.0093	0.6035	0.2820
More detailed Inspection	0.2807	0.0973	0.3322	0.2898

(Source: Author)

Table 3.5 CPT of ‘Vessel group’

Vessel age	Flag	RO	DWT	Low Detention Risk	High Detention Risk
Over20Years	Black (High)	High	Capesize	0.5062	0.4938
Over20Years	Black (High)	High	Handymax	0.4364	0.5636
Over20Years	Black (High)	High	Handysize	0.0012	0.9988
Over20Years	Black (High)	High	Panamax	0.5109	0.4891
Over20Years	Black (High)	High	Small	0.0014	0.9986
…	…	…	…	…	…
…	…	…	…	…	…
…	…	…	…	…	…
5to10years	White	Very Low	Capesize	0.5508	0.4492
5to10years	White	Very Low	Handymax	0.4492	0.5508
5to10years	White	Very Low	Handysize	0.4691	0.5309
5to10years	White	Very Low	Panamax	0.4704	0.5296
5to10years	White	Very Low	Small	0.5111	0.4889

(Source: Author)

Table 3.6 CPT of ‘Inspection group’

			Inspection group	
Port of inspection	Type of inspection	No. of deficiencies	Low	High
Belgium	Expanded	4 to 10	0.9987	0.0013
Belgium	Expanded	More than 10	0.0015	0.9985
Belgium	Expanded	0 to 1	0.9986	0.0014
Belgium	Expanded	1 to 4	0.9987	0.0013
Belgium	Initial	4 to 10	0.9989	0.0011
...	...	...	...	...
UK	Initial	1 to 4	0.9987	0.0013
UK	More Detailed	4 to 10	0.9986	0.0014
UK	More Detailed	More than 10	0.0013	0.9987
UK	More Detailed	0 to 1	0.9990	0.0010
UK	More Detailed	1 to 4	0.9985	0.0015

(Source: Author)

Table 3.7 CPT of ‘Detention’

		Detention	
Vessel group	Inspection group	No	Yes
Low Detention Risk	Low	0.9909	0.0091
Low Detention Risk	High	0.6471	0.3529
High Detention Risk	Low	0.9674	0.0326
High Detention Risk	High	0.5976	0.4024

(Source: Author)

3.3.5 Model result

Based on the CPT of each node, the marginal probability of each child node can be obtained using Equation (3-4). Figure 3.11 shows the result of the BN model using Netica. It indicates that the detention rate of a bulk carrier under inspection is estimated to be 4.52% given the input data covering the period of 2005-2008. If we calculate the detention rate from the database directly, it is 4.57%, which shows a harmony with the result delivered by the model. The model is verified in terms of prediction of detention rate of bulk carriers.

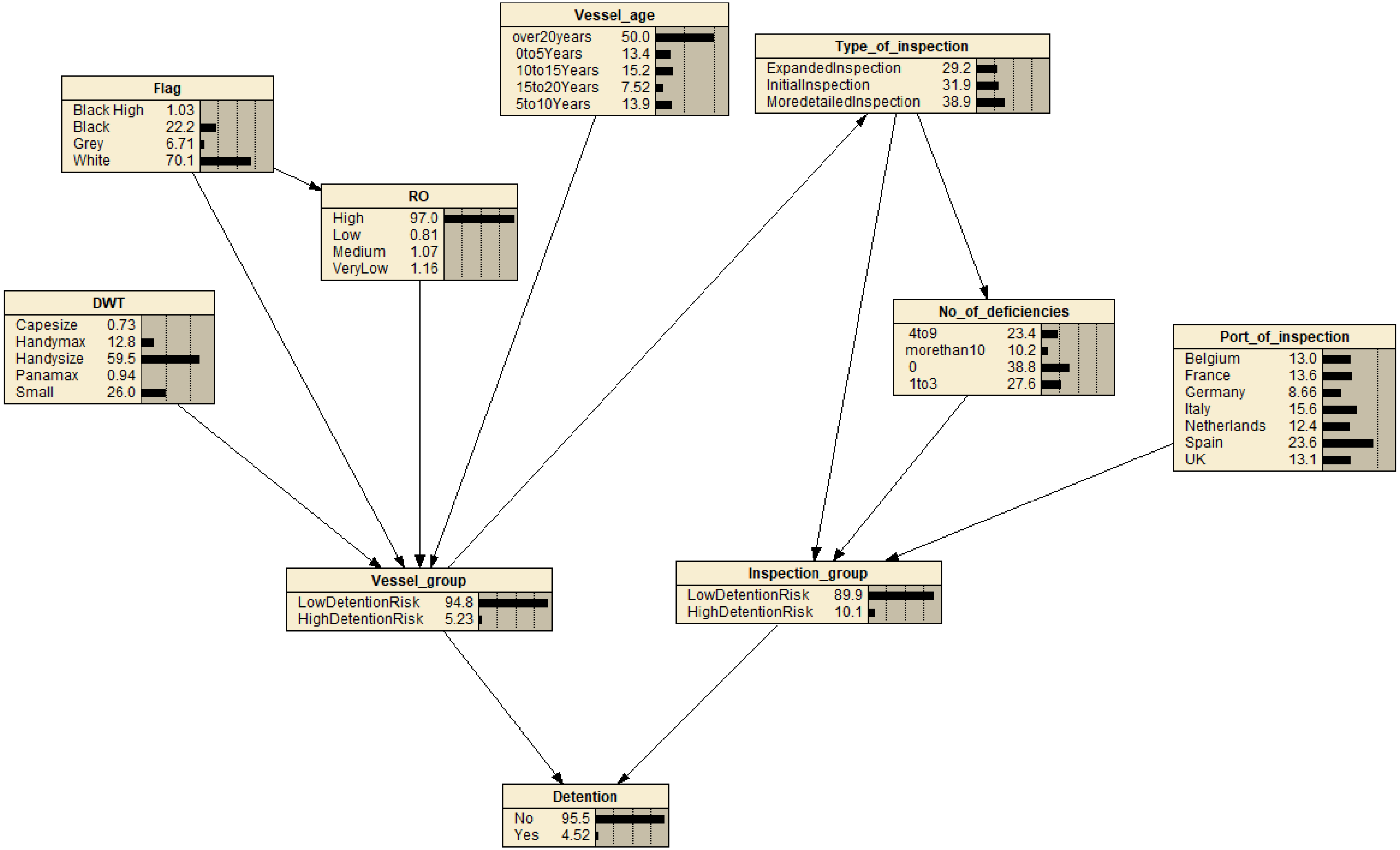

Figure 3.11 Results of BN model

(Source: Author)

3.3.6 Sensitivity analysis

A sensitivity analysis is conducted to analyse influencing degree of risk variables and validate the model to prove its capability of realizing dynamic risk prediction in dynamic environments.

3.3.6.1 Mutual information calculation

According to Equation (3-5) shown in section 3.2.6, mutual information between 'detention' and other risk variables is obtained, which is shown in Table 3.8. The entropy of 'detention' is 0.26555 and the percent column in the table represents the extent of shared information between the other nodes and 'detention'. The values in this column are independent and unrelated to others.

Table 3.8 Sensitivity of other nodes to 'Detention'

Sensitivity analysis			
Node	**Mutual Info**	**Percent**	**Variance of Beliefs**
Inspection group	0.09654	36.4	0.0108729
Number of deficiencies	0.09386	35.3	0.0105047
Type of inspection	0.01464	5.51	0.0008056
Vessel group	0.00140	0.527	0.0001046
RO	0.00025	0.0933	0.0000171
Vessel flag	0.00025	0.0929	0.0000161
DWT	0.00009	0.0331	0.0000053
Vessel age	0.00003	0.0131	0.0000021
Port of inspection	0	0.0007	0.0000001

(Source: Author)

From Table 3.8, it is concluded that:

Firstly, inspection-related risk factors have a stronger relationship with 'detention' than vessel-related variables in general, except 'port of inspection'. Port of inspection has almost no influence on final inspection results.

Secondly, the most significant node is therefore the variable 'Inspection group'. The main reason for this impact is that the parent nodes of 'Inspection group', 'Number of deficiencies' and 'Type of inspection', can change the detention probability more significantly than other first level nodes.

Meanwhile, from Table 4.8, 'Inspection group', 'Number of deficiencies', 'Type of inspection', 'Vessel group', 'RO' and 'Vessel flag' are selected to do further analysis.

3.3.6.2 Scenario simulation - the effects of different variables

Table 3.9 shows the HRI, LRI and TRI value of selected nodes under different scenarios through Equation (3-6).

Take 'Number of deficiencies' as an example to illustrate the calculation process.

1) Set the state '0' to 100%, hence, other states are all at state '0', the detention rate under this scene is obtained through the proposed BN model, which is 1.05 %.

2) Repeat the first step and adjust other states to 100% in turn. The detention rates under each situation are 1.07% (100% '1-3'), 1.10% (100% '4 to 9'), and 35% (100% 'more than 10').

3) Select the lowest detention rate among these situations to calculate LRI. In this case, the scene that state '0' is 100% has the lowest value 1.05%. Therefore, LRI is calculated as follows:

$$LRI = 4.52\% - 1.05\% = 3.47\%$$

4) Similarly, HRI is represented as the maximum increment among these scenarios, which is presented as follows:

$$HRI = 35\% - 4.52\% = 30.48\%$$

5) Finally, TRI is the average value of LRI and HRI.

$$TRI = (3.47\% + 30.48\%) / 2 = 16.98\%$$

As a result, the TRI of 'Number of deficiencies' is 16.98%. The same calculation process goes to other nodes.

In Table 3.9, the first row of each variable represents the normal scenario, and the following rows represent the different scenarios when each state of the variable reaches 100%

occurrence probability respectively. The comparison between TRI of different variables indicates the results of sensitivity analysis – the influence degree of different risk variables.

Table 3.9 TRI of risk variables

<table>
<tr><th colspan="9">Inspection group</th></tr>
<tr><th colspan="2">High</th><th colspan="3">Low</th><th>Detention rate</th><th>HRI</th><th>LRI</th><th>TRI</th></tr>
<tr><td colspan="2">-</td><td colspan="3">-</td><td>4.52%</td><td rowspan="3">31.18%</td><td rowspan="3">3.49%</td><td rowspan="3">17.34%</td></tr>
<tr><td colspan="2">100%</td><td colspan="3">0</td><td>35.7%</td></tr>
<tr><td colspan="2">0</td><td colspan="3">100%</td><td>1.03%</td></tr>
<tr><th colspan="9">Number of deficiencies</th></tr>
<tr><th>0</th><th>1 to 3</th><th>4 to 9</th><th colspan="2">More than 10</th><th>Detention rate</th><th>HRI</th><th>LRI</th><th>TRI</th></tr>
<tr><td>-</td><td>-</td><td>-</td><td colspan="2">-</td><td>4.52%</td><td rowspan="5">30.48%</td><td rowspan="5">3.47%</td><td rowspan="5">16.98%</td></tr>
<tr><td>100%</td><td>0</td><td>0</td><td colspan="2">0</td><td>1.05%</td></tr>
<tr><td>0</td><td>100%</td><td>0</td><td colspan="2">0</td><td>1.07%</td></tr>
<tr><td>0</td><td>0</td><td>100%</td><td colspan="2">0</td><td>1.10%</td></tr>
<tr><td>0</td><td>0</td><td>0</td><td colspan="2">100%</td><td>35%</td></tr>
<tr><th colspan="9">Type of inspection</th></tr>
<tr><th colspan="2">Initial</th><th>Expanded</th><th colspan="2">More detailed</th><th>Detention rate</th><th>HRI</th><th>LRI</th><th>TRI</th></tr>
<tr><td colspan="2">-</td><td>-</td><td colspan="2">-</td><td>4.52%</td><td rowspan="4">3.86%</td><td rowspan="4">3.41%</td><td rowspan="4">7.27%</td></tr>
<tr><td colspan="2">100%</td><td>0</td><td colspan="2">0</td><td>1.11%</td></tr>
<tr><td colspan="2">0</td><td>100%</td><td colspan="2">0</td><td>8.38%</td></tr>
<tr><td colspan="2">0</td><td>0</td><td colspan="2">100%</td><td>4.41%</td></tr>
<tr><th colspan="9">Vessel group</th></tr>
<tr><th colspan="2">High</th><th colspan="3">Low</th><th>Detention rate</th><th>HRI</th><th>LRI</th><th>TRI</th></tr>
<tr><td colspan="2">-</td><td colspan="3">-</td><td>4.52%</td><td rowspan="3">4.35%</td><td rowspan="3">0.24%</td><td rowspan="3">4.59%</td></tr>
<tr><td colspan="2">100%</td><td colspan="3">0</td><td>8.87%</td></tr>
<tr><td colspan="2">0</td><td colspan="3">100%</td><td>4.28%</td></tr>
<tr><th colspan="9">RO</th></tr>
<tr><th>High</th><th>Medium</th><th>Low</th><th colspan="2">Very low</th><th>Detention rate</th><th>HRI</th><th>LRI</th><th>TRI</th></tr>
<tr><td>-</td><td>-</td><td>-</td><td colspan="2">-</td><td>4.52%</td><td rowspan="5">2.79%</td><td rowspan="5">0.07%</td><td rowspan="5">2.86%</td></tr>
<tr><td>100%</td><td>0</td><td>0</td><td colspan="2">0</td><td>4.45%</td></tr>
<tr><td>0</td><td>100%</td><td>0</td><td colspan="2">0</td><td>5.95%</td></tr>
<tr><td>0</td><td>0</td><td>100%</td><td colspan="2">0</td><td>7.11%</td></tr>
<tr><td>0</td><td>0</td><td>0</td><td colspan="2">100%</td><td>7.31%</td></tr>
<tr><th colspan="9">Vessel age</th></tr>
<tr><th>0 to 5</th><th>5 to 10</th><th>10to15</th><th>15to20</th><th>Over20</th><th>Detention rate</th><th>HRI</th><th>LRI</th><th>TRI</th></tr>
<tr><td>-</td><td>-</td><td>-</td><td>-</td><td>-</td><td>4.52%</td><td rowspan="6">0.14%</td><td rowspan="6">0.16%</td><td rowspan="6">0.3%</td></tr>
<tr><td>100%</td><td>0</td><td>0</td><td>0</td><td>0</td><td>4.36%</td></tr>
<tr><td>0</td><td>100%</td><td>0</td><td>0</td><td>0</td><td>4.37%</td></tr>
<tr><td>0</td><td>0</td><td>100%</td><td>0</td><td>0</td><td>4.36%</td></tr>
<tr><td>0</td><td>0</td><td>0</td><td>100%</td><td>0</td><td>4.43%</td></tr>
<tr><td>0</td><td>0</td><td>0</td><td>0</td><td>100%</td><td>4.66%</td></tr>
</table>

(Source: Author)

Accordingly, based on the results obtained in Table 3.9, the most important variables can be listed as follows:

Inspection group > Number of deficiencies > Type of inspection > Vessel group > RO > Vessel age

As ‘inspection group’ and ‘vessel group’ are class variables which do not exist in PSC inspection records, ‘Number of deficiencies’ is in fact the most important risk factor, followed by ‘type of inspection’, ‘RO’ and ‘Vessel age’. This result indicates sub-standard performance of inspection-related items (Number of deficiencies, type of inspection, etc.) is more likely to lead to detention than unqualified intrinsic attributes of vessels (vessel age, dwt, RO, etc.).

Meanwhile, the BN model in this study can be used to calculate detention rate of bulk carriers under different situations, serving as a dynamic prediction tool. Such a tool not only helps port authorities to test their policies, but also urges ship owners to improve their vessels accordingly.

In addition, the floating range of different variables on detention rate can also be obtained from this table.

3.3.7 Model validation

To validate the model, another sensitivity analysis is carried out by investigating the detention rate of the minor change given different risk variables. By selecting ‘Inspection group’ as the first node, the state generating the highest detention rate is increased by 10%, while the state generating lowest detention rate is decreased by 10%. This change is denoted as ‘~10%’ in this study. Once the updated detention rate is obtained, the same change is applied to next node and the combined detention rate is calculated. The sensitivity analysis continues in the same manner until all nodes are included. The following Table 3.10 presents the results of this sensitivity analysis.

Table 3.10 Detention rate of minor change in variables

Inspection group	Number of deficiencies	Type of inspection	Vessel group	RO	Vessel age	Detention rate
-	-	-	-	-	-	4.52%
~10%	-	-	-	-	-	7.98%
~10%	~10%	-	-	-	-	7.99%
~10%	~10%	~10%	-	-	-	8.55%
~10%	~10%	~10%	~10%	-	-	9.14%
~10%	~10%	~10%	~10%	~10%	-	9.59%
~10%	~10%	~10%	~10%	~10%	~10%	9.71%

(Source: Author)

The first row shows the original detention rate and the rest of the table presents the updated detention rates by changing risk variables continuously. Through comparing the updated results with the initial detention rates, it is claimed that the model is proved to be in line with Axiom 1.

As to Axiom 2, it can be examined by comparing the initial detention rate with reassigned detention rates, which can be regarded as the evidence and sub-evidence. From Table 3.9, the detention rate is gradually increasing along with the continuous variation of risk variables, which proves the model is sound in line with Axiom 2.

In general, the model developed is proved reasonable and reliable. It can be used to predict the detention rate of PSC inspection of the Paris MoU when any new evidence is entered. Meanwhile, the results of the model, as well as the variation law of detention rate, can be used by port authorities to improve their policies and ship owners to increase their passing rate.

Although based on the inspection records before the implementation of NIR, it still has great referential significance. Additionally, it is also important to illustrate the model to help us better understand the significance and influence of NIR.

3.4 BN MODEL FOR PSC INSPECTION AFTER THE IMPLEMENTATION OF NIR – ‘POST-NIR BN MODEL’

After the implementation of NIR, the PSC inspection system experienced huge transformation. SRP, Company performance calculator, ‘fair share’ scheme and the new THETIS data system are some of the great efforts made to ensure the efficient operation of the PSC inspection system. Reflecting the risk assessment model, the BN of this period is different from the former one.

3.4.1 Data acquisition

Collected from the Paris MoU online inspection database, this time 49, 328 inspection records from 2015-2017 are extracted to form the foundation of the research. To maintain consistency, bulk carriers are still selected as the research target, which is helpful for the comparative analysis conducted in Chapter 4.

According to the statistics, 7,252 inspection records are related to bulk carriers, occupying 14.7% of the total amounts. Compared to 15.62% occupancy in the former model, the status of bulk carriers in PSC inspections largely remains the same.

3.4.2 Variable identification

The variables in ‘Post-NIR’ BN are also identified from the Paris MoU online inspection database. However, the identified risk factors are slightly different from the ones in ‘Pre-NIR’ BN, including vessel flag, vessel age, company performance, type of inspection, port of inspection, date of inspection, number of deficiencies, and detention. Among these variables, ‘Company performance’ and ‘Inspection date’ are two new-added risk factors. In addition, ‘Company performance’ is the factor that can best represent the specialty of the NIR, which also highlights the novelty of the ‘Post-NIR’ BN model.

Here is an explanation of them with a particular reference to their state definitions.

(1) Company performance

Since the implementation of NIR, most ISM companies have raised their adoption policies to maintain their reputation in spite of facing possible toll losses. As a result, company performance, one of the parameters to determine the SRP, is currently one of the most relevant indexes reflecting vessel safety conditions and inspection results.

Company performance takes account of the detention and deficiency history of all ships in a company's fleet while that company was the ISM Company for the ship. Companies are ranked as having a very low, low, medium or high performance. The calculation is made daily based on a running 36-month period. There is no lower limit for the number of inspections needed to qualify except a company with no inspections in the last 36 months will be given a "medium performance".

Table 3.11 presents the standard of classification of company performance from the Paris MoU official website.

Table 3.11 Company performance classification standard

<table>
<tr><th>Detention Index</th><th>Deficiency Index</th><th>Company Performance</th></tr>
<tr><td>Above Average</td><td>Above Average</td><td>Very Low</td></tr>
<tr><td>Above Average</td><td>Average</td><td rowspan="4">Low</td></tr>
<tr><td>Above Average</td><td>Below Average</td></tr>
<tr><td>Average</td><td>Above Average</td></tr>
<tr><td>Below Average</td><td>Above Average</td></tr>
<tr><td>Average</td><td>Average</td><td rowspan="3">Medium</td></tr>
<tr><td>Average</td><td>Below Average</td></tr>
<tr><td>Below Average</td><td>Average</td></tr>
<tr><td>Below Average</td><td>Below Average</td><td>High</td></tr>
</table>

(Source: Paris MoU)

In a word, this variable has four states: 'High', 'Medium', 'Low' and 'Very low'.

Because the inspection records online only have the number of the ISM company of each vessel, hence we calculate the company performance of each inspection manually through the 'company performance calculator' online.

(2) Inspection date

This variable is set up in order to test the influence of time. Due to the different situations and environments port authorities may face each year, the policy and regulations of PSC will change accordingly, affecting the passing rates of vessels being inspected at ports.

It has three states apparently, '2015', '2016' and '2017'.

In addition, two vessel-related variables, RO and DWT, are not taken into account this time. This is because the new Paris MoU online inspection database after NIR does not display the two variables on the 'search' page any more. Hence, the web crawler software we used is unable to acquire their information and thus they are excluded from the BN model.

Other variables remain the same with the 'Pre-NIR' BN model and the state definitions of these variables also do not change. Table 3.12 shows the state classification of each variable in 'Post-NIR' model.

Table 3.12 Identified variables in PSC inspections from 2015-2017

VARIABLE	**STATE**
Vessel flag	White, Grey, Black, Black (high risk)
Vessel age	0 to 5 years, 5 to10 years, 10 to15 years, 15 to 20 years, over 20 years
Company performance	High, Medium, Low, Very low
Type of inspection	Initial inspection, More detailed inspection, Expanded inspection
Port of inspection	Belgium, Canada, France, Germany, Greece, Italy, Netherlands, Spain, UK
Date of inspection	2015, 2016, 2017
Number of deficiencies	0, 1 to 3, 4 to 9, more than 10
Inspection group	High detention Risk, Low detention Risk
Vessel group	High detention Risk, Low detention Risk
Detention	Yes, No

(Source: Author)

** The justification of the selection of the variables and their grades refers to the former section.*

Similarly, two mediating level risk variables, 'vessel group' and 'inspection group', are introduced based on the principle of divorcing approach (Jensen, 2001; Yang, et al., 2018) to avoid that the size of CPTs are too large to effectively control. The classification criterion of the two nodes remains the same with 'Pre-NIR' BN.

3.4.3 BN construction

Through the Netica software, the resulting BN structure from TAN learning is presented in Figure 3.12. The optimizing process of network construction is omitted here, because it is identical to the process illustrated in section 3.3.3.

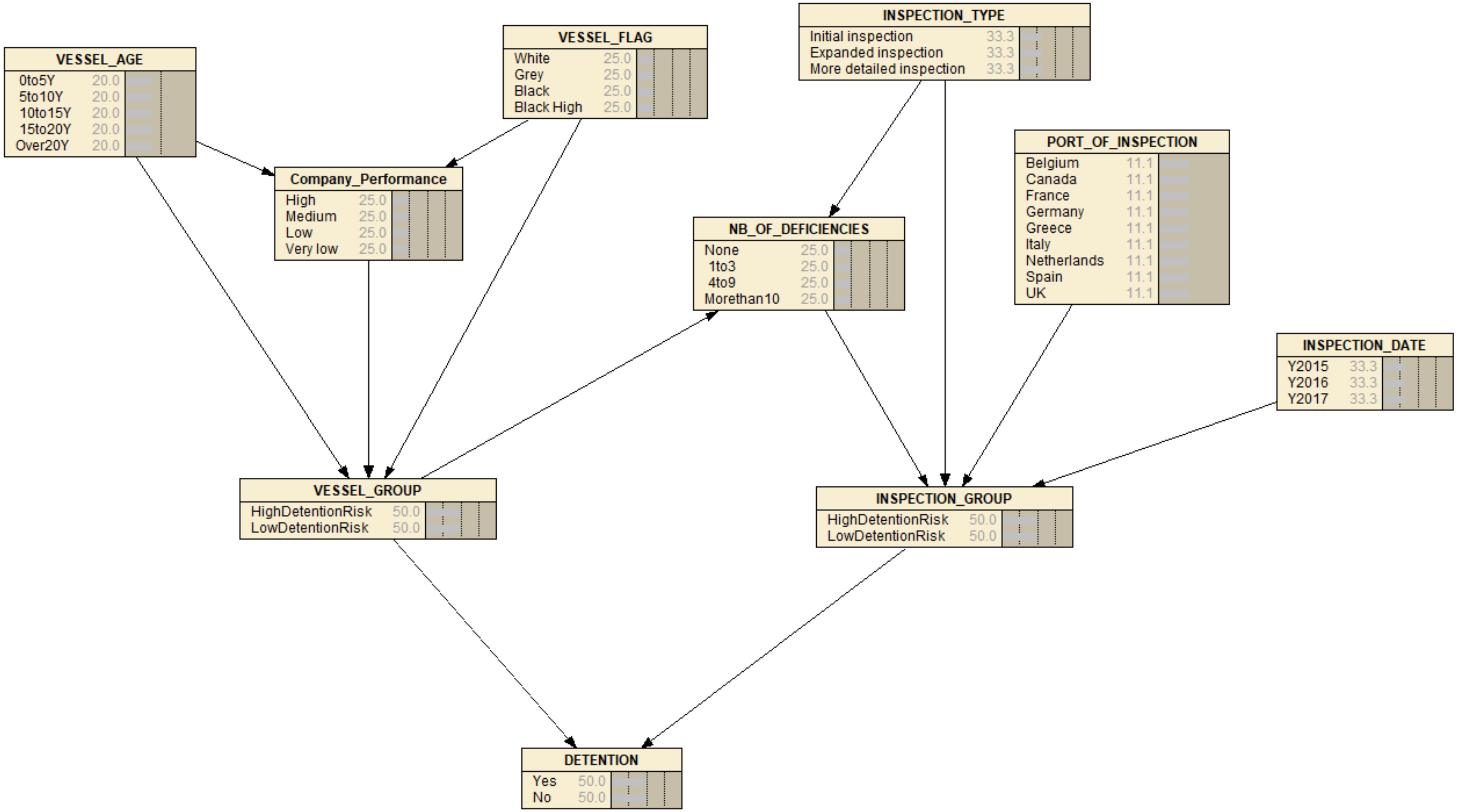

Figure 3.12 The structure of BN

(Source: Author)

Compared to the ‘Pre-NIR’ BN model, the biggest difference between the two models lies in the removal of the links pointed from ‘vessel group’ to ‘Inspection type’, which is the connection between vessel-related variables and inspection-related variables. Instead, a link from ‘vessel group’ to ‘number of deficiencies’ now acts as the bond connecting the two parts. The reason for this change is that the inspection type of a particular vessel under NIR is currently influenced by the last PSC inspection results this vessel experienced. Hence, the ‘vessel group’ node, which represents the vessel status of this time, is no longer the parent node of ‘inspection type’ in our model. In order to maintain the connection between vessel-related variables and inspection-related variables, the link between ‘vessel group’ and ‘number of deficiencies’ is set as the new bond, because the overall condition of the vessel has crucial influence on the number of deficiencies detected during a PSC inspection.

3.4.4 CPT distribution and risk prediction

After confirming the structure of the BN, the conditional probabilities of the nodes are required to model the uncertainties of risk variables. Through gradient descent approach mentioned above, the CPTs can be obtained and shown in Appendix 2.

3.4.5 Model result

Figure 3.13 shows the result of detention analysis based on the BN model. It indicates that the detention rate of a bulk carrier is estimated to be 3.25% given the input data covering the period of 2015-2017. If we calculate the detention rate from the database directly, it is 3.23%, which shows a harmony with the result delivered by the model. The model is verified in terms of prediction of detention rate of bulk carriers.

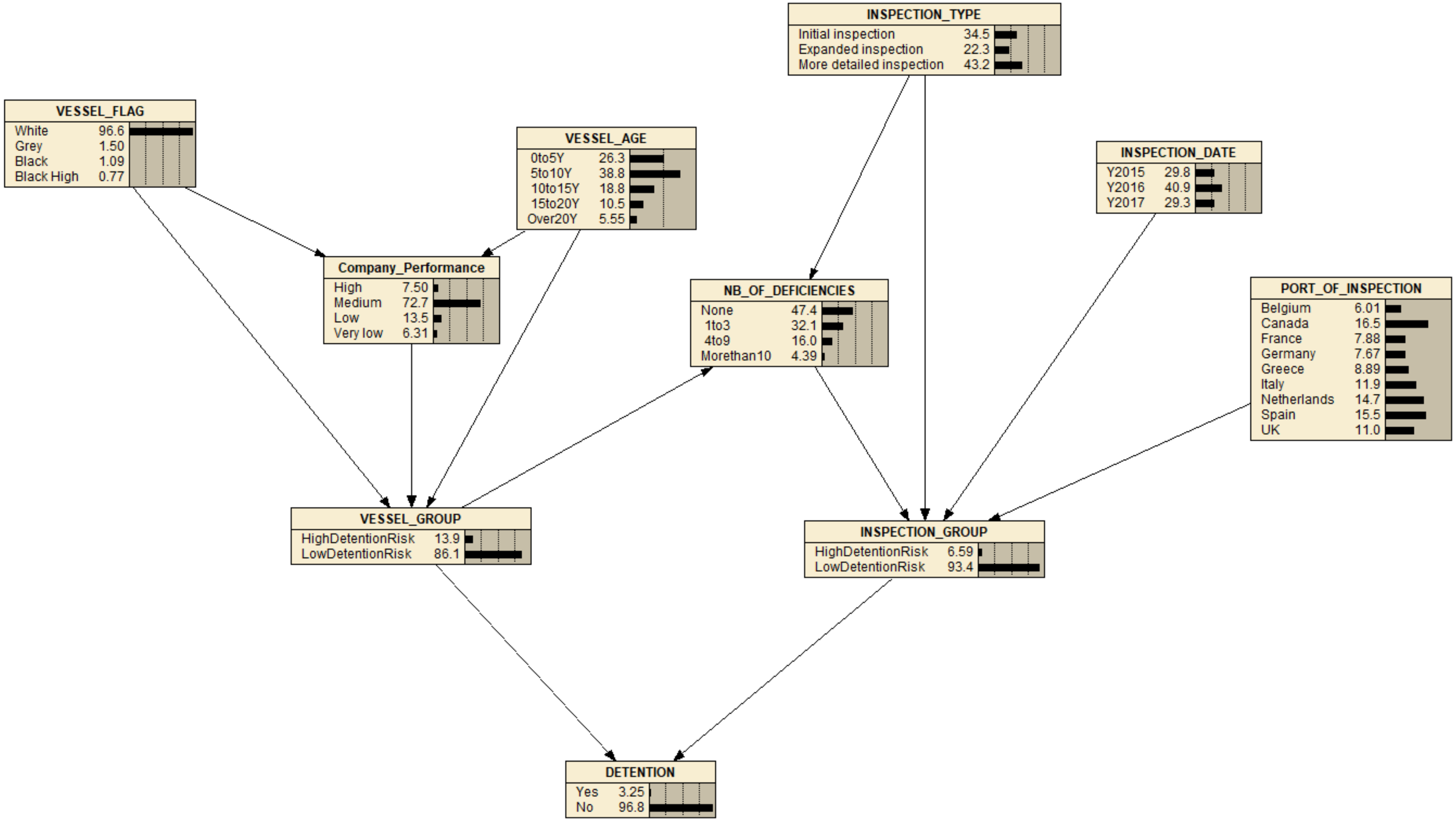

Figure 3.13 ‘Post-NIR’ BN

(Source: Author)

3.4.6 Sensitivity analysis and model validation

The sensitivity analysis of 'Post-NIR' BN also consists of two parts, analysis on mutual information and scenario simulation.

3.4.6.1 Analysis of Mutual information

Table 3.13 presents the value of mutual information between different nodes and target node 'detention'. Due to the variation of network structure, the results of sensitivity analysis on 'Post-NIR' BN through the comparison of mutual information change accordingly are different from those in 'Pre-NIR' model, which are displayed in section 4.3.6

Table 3.13 Mutual information between other nodes and 'Detention'

Sensitivity analysis			
Node	**Mutual Info**	**Percent**	**Variance of Beliefs**
Detention	0.20672	100	0.0314319
Inspection group	0.06135	29.7	0.0061904
Number of deficiencies	0.04891	23.7	0.0050644
Vessel group	0.03622	17.5	0.0024699
Company Performance	0.02659	12.9	0.0016154
Vessel age	0.00638	3.09	0.0003219
Type of inspection	0.00579	2.8	0.0002493
Port of inspection	0.00110	0.531	0.0000505
Vessel flag	0.00036	0.174	0.0000208
Inspection date	0.00008	0.0369	0.0000033

(Source: Author)

Compared to Table 3.8, the mutual information related to 'inspection group', 'number of deficiencies', 'type of inspection' decrease, indicating the relationships between these variables and 'detention' become weaker, while the mutual information related to 'vessel group', 'vessel age', 'port of inspection' increase, representing stronger relationships of these variables with 'detention'. In general, more risk factors are closely connected with 'detention' than ever.

At the same time, the conclusions acquired from Table 3.8 are also reasonable for Table 3.13.

1) Inspection-related risk factors still overwhelm vessel-related factors in terms of relationship with ‘detention’.

2) ‘Inspection group’ continues to be the most significant variable, followed by ‘Number of deficiencies’.

3) ‘Port of inspection’, along with ‘vessel flag’ and new added factor ‘inspection date’, become the lowest priority parts. Although compared to the ‘Pre-NIR’ period, ‘port of inspection’ and ‘vessel flag’ increased dramatically, for example, ‘port of inspection’ has risen from 0.0007% to 0.531% (more than 700 times increase), the relationships between them and ‘detention’ are still too weak when comparing with other nodes. Therefore, they are not selected to do further analysis. In a word, the selection of nodes is a result of both horizontally and vertically comparison.

The detailed information of the comparison between the results of sensitivity analysis of two models is presented in Chapter 4, which is used to demonstrate the change and significance brought about by the implementation of NIR.

3.4.6.2 Scenario simulation - the effects of different variables

Table 3.14 shows the TRI value of selected nodes under different scenarios. Because of little influence on the ‘detention’ compared to other nodes, ‘Port of inspection’, ‘Vessel flag’ and ‘Inspection date’ are therefore not taken into our consideration.

Table 3.14 TRI of risk variables

Inspection group					
High	**Low**	**Detention rate**	**HRI**	**LRI**	**TRI**
-	-	3.25%	29.65%	2.09%	***15.87%***
100%	0	32.9%			
0	100%	1.16%			

Number of deficiencies							
None	**1 to 3**	**4 to 9**	**More than 10**	**Detention rate**	**HRI**	**LRI**	**TRI**
-	-	-	-	3.25%	32.75%	2.21%	***17.48%***
100%	0	0	0	1.04%			
0	100%	0	0	1.41%			
0	0	100%	0	4.52%			
0	0	0	100%	36%			

Vessel group					
High	**Low**	**Detention rate**	**HRI**	**LRI**	**TRI**
-	-	3.25%	12.35%	1.99%	***7.17%***
100%	0	15.6%			
0	100%	1.26%			

Company Performance							
High	**Medium**	**Low**	**Very low**	**Detention rate**	**HRI**	**LRI**	**TRI**
-	-	-	-	3.25%	11.65%	1.93%	***6%***
100%	0	0	0	1.49%			
0	100%	0	0	1.32%			
0	0	100%	0	9.17%			
0	0	0	100%	14.9%			

Vessel age								
0to5Y	**5to10Y**	**10to15Y**	**15to20Y**	**over20Y**	**Detention rate**	**HRI**	**LRI**	**TRI**
-	-	-	-	-	3.25%	4.74%	1.65%	***3.20%***
100%	0	0	0	0	1.60%			
0	100%	0	0	0	3.15%			
0	0	100%	0	0	2.50%			
0	0	0	100%	0	6.56%			
0	0	0	0	100%	7.99%			

Type of inspection						
Initial	**Expanded**	**More detailed**	**Detention rate**	**HRI**	**LRI**	**TRI**
-	-	-	3.25%	2.49%	1.79%	***2.24%***
100%	0	0	1.46%			
0	100%	0	5.74%			
0	0	100%	3.40%			

(Source: Author)

Through comparing TRI values, the variables are listed in the sequence of the degree of the influence on 'detention', which is shown as follows:

Number of deficiencies > Inspection group > Vessel group > Company performance > Vessel age > Type of inspection

The conclusions obtained from scenario simulation of the 'Pre-NIR' model still take effect, for example, inspection-related risk factors should be paid more attention than vessel-related factors because the influence value of the former group is much greater than the latter one; 'Number of deficiencies' remains its dominating position in this list.

However, at the same time, it is obvious to find that the sequence is different from the previous one, i.e. Number of deficiencies is the most influencing variable under NIR; the influence of 'Company performance' is only less than 'Number of deficiencies' among the whole risk factors group (except two dummy variables). All these changes indicate that the implementation of NIR has indeed affected the PSC inspection system.

Chapter 4 will present a comparative analysis between Table 4.8 and Table 4.12 from different angles to illustrate the influence of the new inspection regime.

3.4.7 Model validation

The principle of conducting model validation is the same as Section 3.3.7. By selecting 'Number of deficiencies' as the first node, the state generating highest detention rate is increased by 10%, while the state generating lowest detention rate is decreased by 10%. This change is denoted as '~10%' in this study. Once the updated detention rate is obtained, the same change is applied to the next node and the combined detention rate is calculated. In this model, the sequence is 'Number of deficiencies – Inspection group – Vessel group – Company performance – Vessel age – Type of inspection'.

Table 3.15 presents the results of the minor changes given different variables.

Table 3.15 Detention rate of minor change in variables

Number of deficiencies	Inspection group	Vessel group	Company performance	Vessel age	Type of inspection	Detention rate
-	-	-	-	-	-	3.25%
~10%	-	-	-	-	-	6.74%
~10%	~10%	-	-	-	-	10.20%
~10%	~10%	~10%	-	-	-	13.40%
~10%	~10%	~10%	~10%	-	-	16.5%
~10%	~10%	~10%	~10%	~10%	-	18.7%
~10%	~10%	~10%	~10%	~10%	~10%	21%

(Source: Author)

The first row shows the original detention rate and the rest of the table presents the updated detention rates by changing risk variables continuously. Through comparing the updated results with the initial detention rates, it is claimed that the model is proved to be in line with Axiom 1.

As to Axiom 2, it can be examined by comparing the initial detention rate with reassigned detention rates, which can be regarded as the evidence and sub-evidence. From Table 3.14, the detention rate is gradually increasing along with the continuous variation of risk variables, which proves the model is sound in line with Axiom 2.

In general, the 'Post-NIR' BN model is reasonable and reliable. Since the implementation of NIR, this is the first time that a risk assessment model is developed to help analyse the new inspection system and the change brought by the new regime. Additionally, it can also serve as a dynamic prediction tool for port authorities and ship owners to estimate the detention rate of PSC inspection of the Paris MoU when any new evidence is entered. It can work as a screening tool for port authorities to check whether the inspected vessel is legal or not. Those having higher estimated detention rates should be inspected in detail to determine the exact detention time, and other vessels can be paid less attention and less resource. For ship owners, they can estimate the inspection rate of their vessels according to the vessel status and the expected inspection details to see whether their vessels need to be maintained and improved in advanced.

Section 3.5 will illustrate how the proposed model works in real life to help different stakeholders in PSC inspections.

3.5 RESEARCH IMPLICATIONS – ANALYSIS ON THE PERFORMANCE OF ISM COMPANIES

As the newly added risk variables, the performance of ISM companies presents its great influence on inspection results based on the above analysis, demonstrating the important role of ISM companies in the current PSC practice.

For ISM companies, when deciding whether to adopt a vessel, they need to do many preparation works on this vessel. A sub-standard vessel may reduce its performance level recorded at Paris MoU, and then further influence its reputation in this area and do harm to its potential revenue. Hence, ISM companies should pay attention to those variables that are closely related to their performance level indicator at Paris MoU.

In this section, a brief analysis is conducted to tell ISM companies which variables they should focus on when selecting vessels based on the proposed BN model.

Table 3.16 presents the mutual information between 'Company performance' and other variables in 'Post-NIR' BN model. Because mutual information describes the strength of relationship between variables, which can be seen as the degree of impact, it is helpful to provide suggestions for ISM companies. Additionally, the relationships here are undirected, which means company performance is not always the affected variable.

Table 3.16 Mutual information between 'Company performance' and other variables

Node	Mutual information
Company performance	1.25605 (Entropy)
Vessel group	0.38650
Vessel age	0.06074
Detention	0.02659
Number of deficiencies	0.02417
Inspection group	0.01282
Vessel flag	0.01048
Inspection date	0.00000
Port of inspection	0.00000
Inspection type	0.00000

(Source: Author)

According to Table 3.16, several suggestions can be made to ISM companies.

1) ‘Vessel group’ has the strongest relationship with company performance. The influence brought by ‘Vessel group’ is much larger than other risk variables. ISM companies should give the highest priority to the risk level of vessels when making adoption decisions. A low risk vessel basically means the company performance indicator at PSC inspection is high or medium, as indicated in Figure 3.14. On the contrary, a high-risk vessel largely leads to a low/very low performance level record in the PSC inspection database, as shown in Figure 3.15.

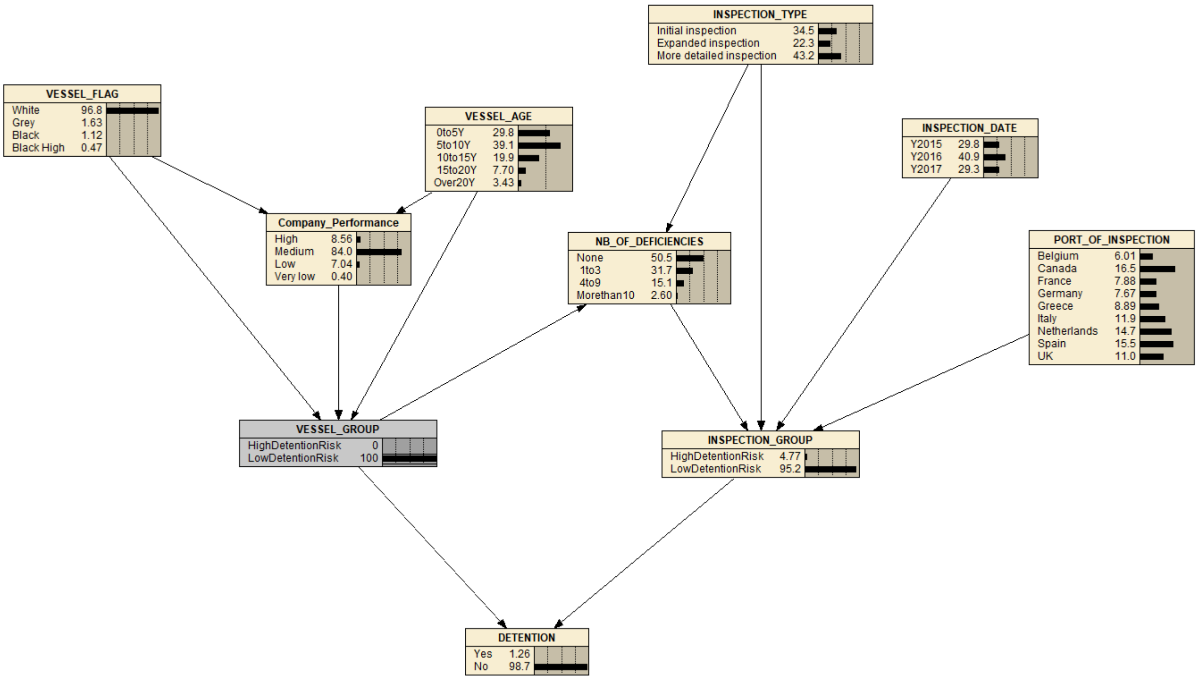

Figure 3.14 Low vessel-related risk level vessels

(Source: Author)

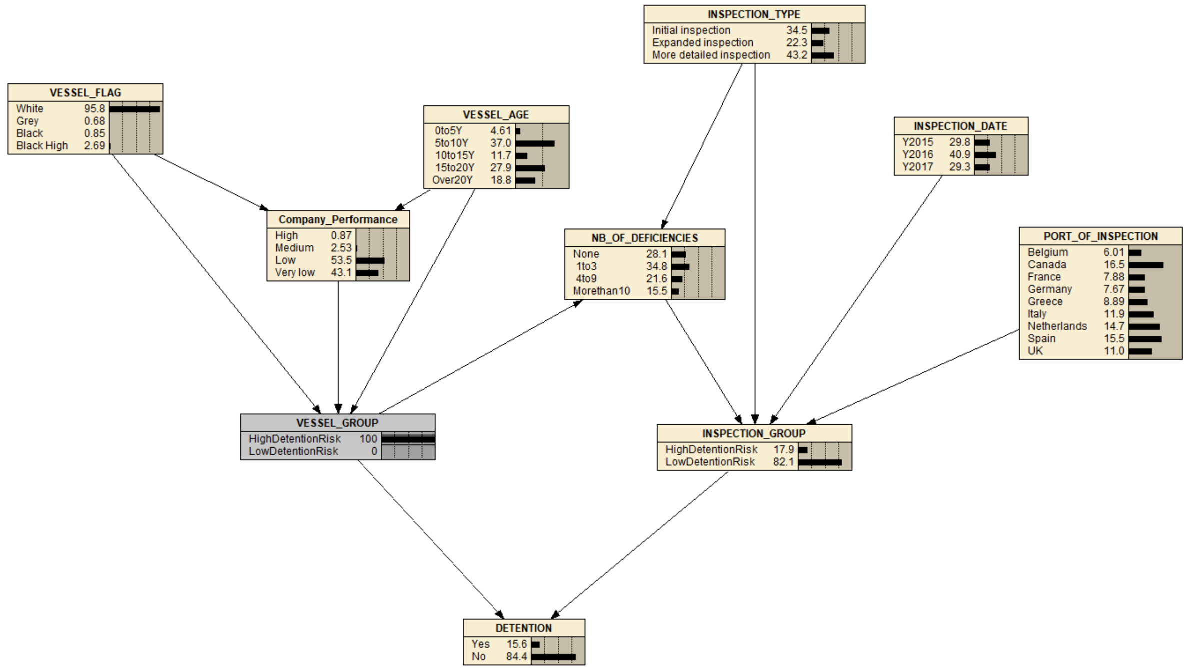

Figure 3.15 High vessel-related risk level of vessels

(Source: Author)

In practice, the risk level of vessels is reflected by the inspection records, or the SRP indicator, which should be taken into consideration by ISM companies.

2) For ISM companies, vessel-related variables, i.e. vessel age, vessel flag, and other variables not listed in BN, have closer relationship with ‘company performance’ than inspection-related variables. These variables represents every aspect of the risk level of vessels.

3) Among the vessel-related variables, vessel age is the most influential variables. Figure 3.16 and 3.17 illustrate the company performance level when the vessel age is at ‘0-5’ and ‘more than 20’ states, and it is not surprising to find older vessels will reduce the company performance indicator largely, thus need to be treated seriously.

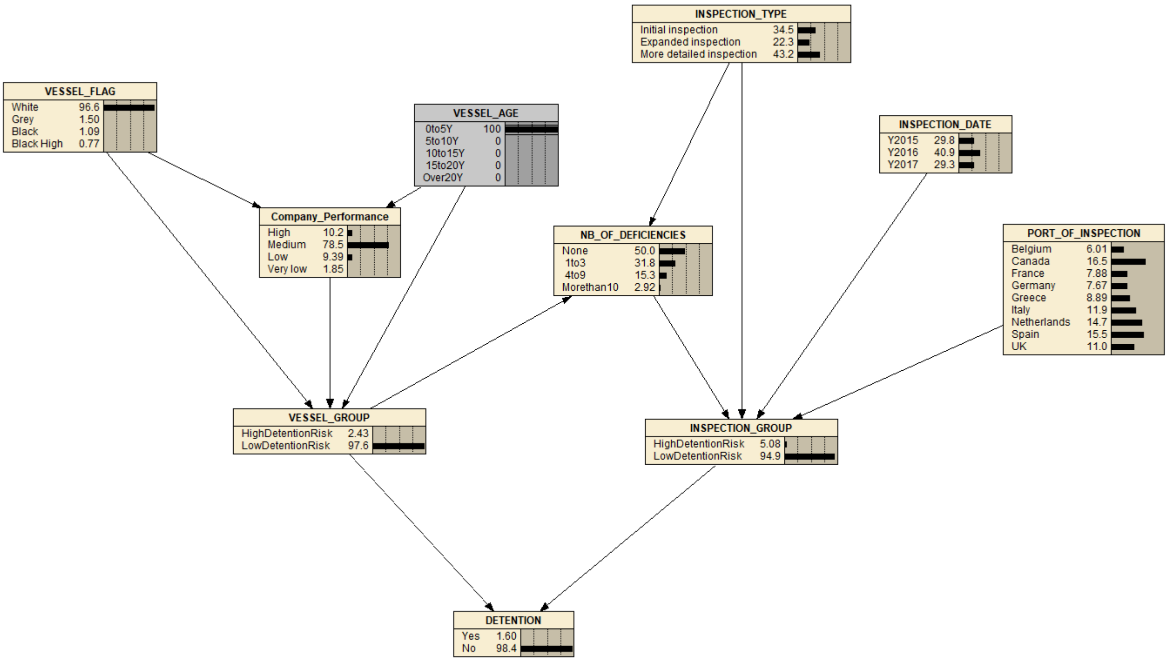

Figure 3.16 Vessels at 0-5 years

(Source: Author)

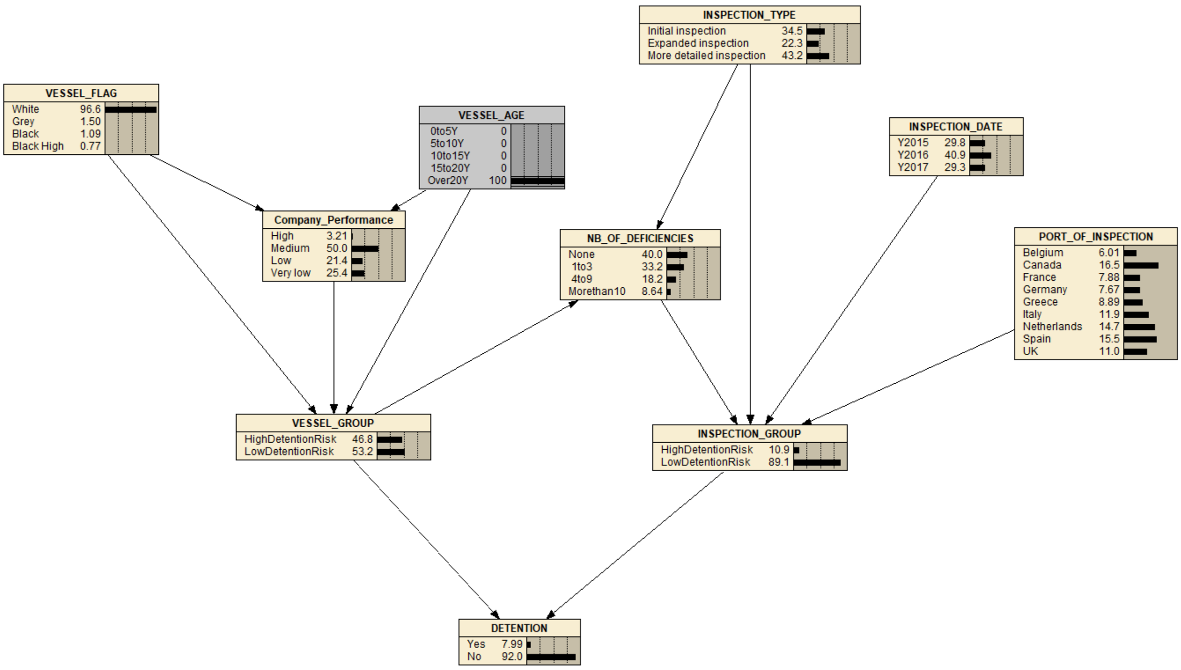

Figure 3.17 Vessels over 20 years

(Source: Author)

4) Inspection-related variables have almost no influence on the company performance. This phenomenon is reasonable because the selection of ISM companies happens before the occurrence of PSC inspections, hence the ISM companies are unable to evaluate its performance level based on these factors.

One interesting thing is that ‘Inspection group’ has weak relationship with company performance, this can be viewed as the influence brought by company performance on the risk level of inspection. Although the influence is weak, it still proves that the performance level of ISM companies can affect the inspection risk of vessels.

5) The mutual information calculation in Table 3.16 once again demonstrate the influence brought by company performance on detention, urging ISM companies to improve their adoption criteria and select more high-quality vessels. The detailed information of this influence can be found in Section 4.3.2.

3.6 RESEARCH IMPLICATIONS - MODEL APPLICATIONS IN REAL CASES

In this section, some real cases are simulated to illustrate how the proposed model can help both port authorities and ship owners in PSC inspections. The information in the cases is set based on the real inspection records in the Paris MoU online database.

In order to demonstrate the practical significance of the model, as well as make the illustration more convincing, the ‘Post-NIR’ model is selected to do the case studies. The reason is that the ‘Pre-NIR’ model is constructed based on the past inspection records, thus is no longer suitable in today’s environment.

3.6.1 Case I

A bulk carrier was inspected at the Port of Liverpool on 01/12/2017, and the information of this inspection is shown as follows:

1) Vessel age: 3 years

2) Vessel flag: Marshall Islands (White list)

3) Company performance: Medium (Atlantska Plovidba dd, IMO number 0096086)

4) Inspection date: 2017

5) Inspection: initial inspection

6) Port: Liverpool (UK)

7) Number of deficiencies identified: 1

To determine whether this vessel meets the requirement of PSC regulations, the port authority of Liverpool should input the information of this inspection into the proposed ‘Post-NIR’ BN model, which is shown in Figure 3.14. The result indicated the detention rate was 0.54%, demonstrating this vessel was standard and should not be detained.

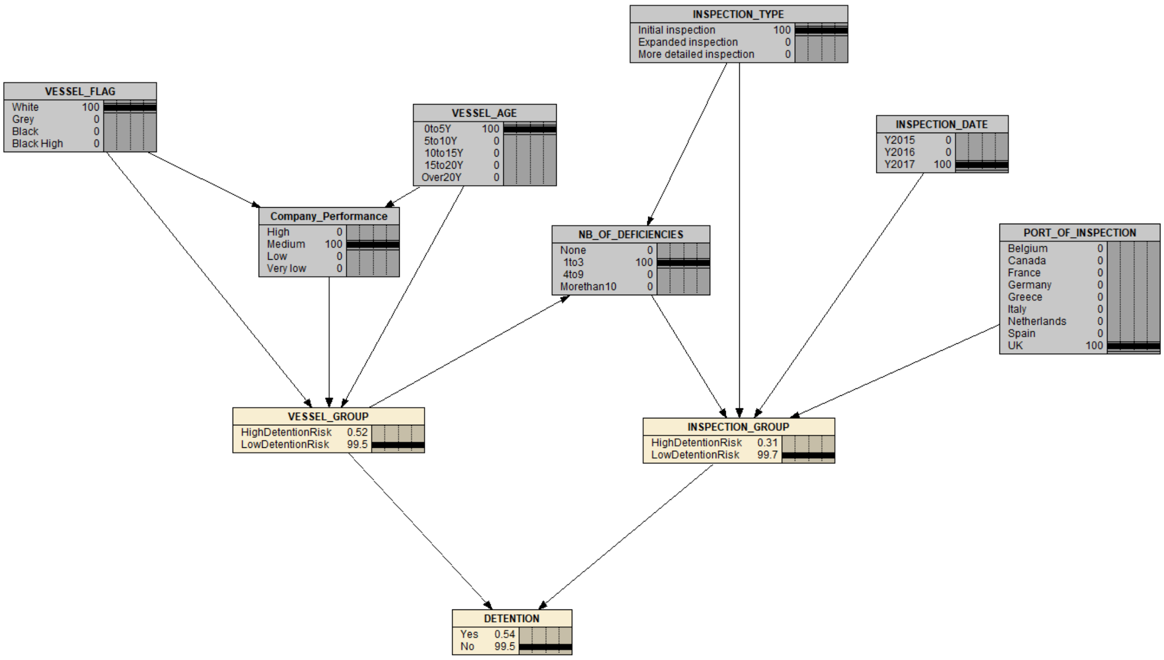

Figure 3.18 Inspection result prediction of Case I

(Source: Author)

In fact, the inspection record of case I in the Paris MoU online database showed this vessel passed the inspection, which coincides with the model result, illustrating the effectiveness of the model in PSC inspections.

3.6.2 Case II

The relevant information gathered from a bulk carrier that was to be inspected at the Port of Gibraltar on 06/10/2017 was:

1) Vessel age: 12 years

2) Vessel flag: Panama (White list)

3) Company performance: Very low (Irika Shipping SA, IMO number 5022255)

4) Inspection date: 2017

5) Inspection: Expanded inspection

6) Port: Gibraltar

7) Number of deficiencies identified: 16

3.6.2.1 Perspective from the port authority of Gibraltar

Port authorities aim to regulate the behaviour of ship owners to avoid potential accidents and ensure ship safety through their PSC inspections. The vessels at high risk need to be identified and detained. In this case, the port authority of Gibraltar could input the relevant information related to this inspection into the proposed BN model, the result indicated the detention rate was 58.5% under this condition in Figure 3.15. Compared to the normal detention rate 3.52%, the detention rate of this vessel was almost 17 times higher. Meanwhile, it was 108 times higher than the detention rate of the standard vessel in Case I (0.54%). Therefore, this vessel was sub-standard and port authority of Gibraltar needed to detain this vessel to avoid potential accidents at sea.

In fact, if we check the result of this inspection from the Paris MoU database, this vessel is indeed detained, proving the effectiveness and accuracy of the model when making decisions for port authorities.

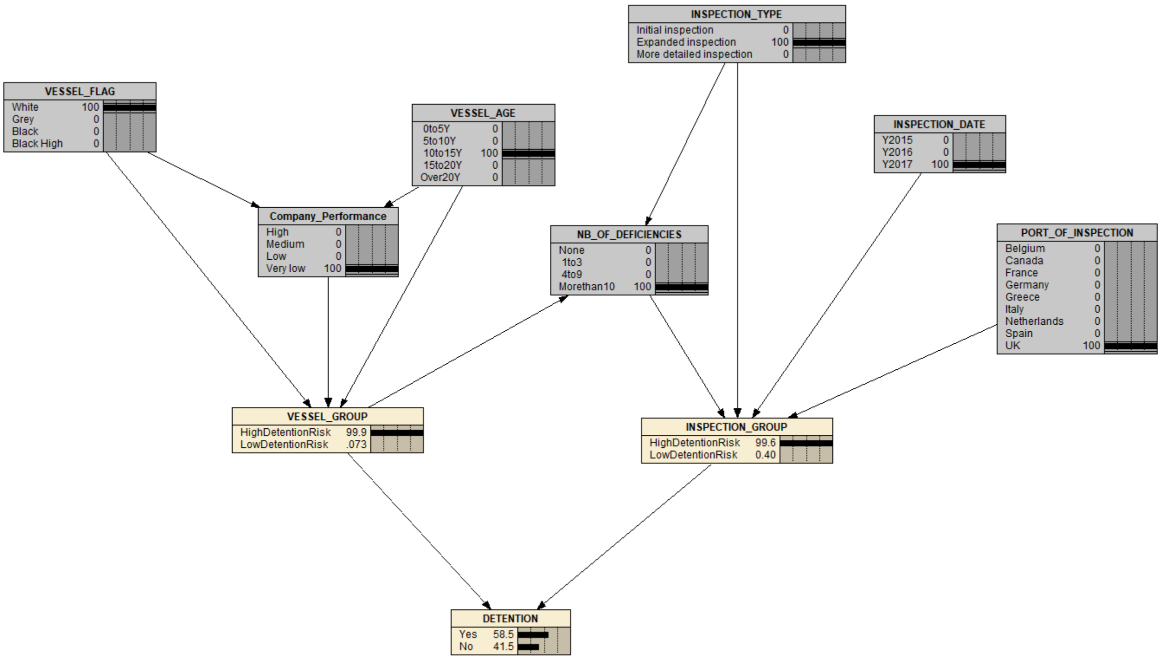

Figure 3.19 Perspective of Gibraltar Port authority

(Source: Author)

3.6.2.2 Perspective of the ship owner

Once this ship owner was informed that their vessel was detained, they needed to address all the identified deficiencies. If the vessel were detained twice in succession, it would have a very high probability to be banned by the Paris MoU. Different from port authorities, ship owners care more for profits and thus evaluate whether the investment on repair/maintenance could help them avoid detention next time. In this regard, the BN model is helpful to rationalize their decisions.

When the ship owner fixed the deficiencies according to the detention report and retains the vessel at a high quality status by reducing the number of deficiencies at a low level, e.g. ‘1 to 3’, it can be accepted and managed by an ISM company that performs much better. When it was inspected in the Port of Gibraltar in this case, even under the worst situation with the combination of low company performance and expanded inspection type, the likelihood for its detention was only 0.54% shown in Figure 3.16. Therefore, it would strongly motivate the owner to rectify the deficiencies given it was proved to be beneficial.

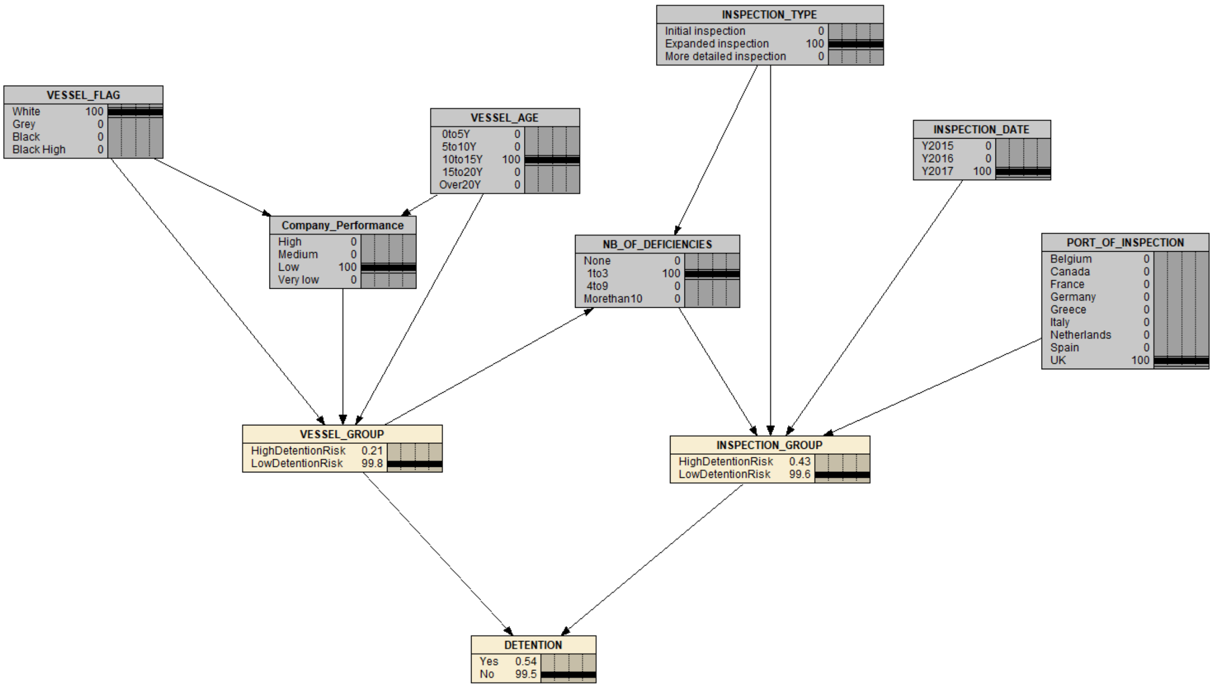

Figure 3.20 Perspective of the ship owner

(Source: Author)

CHAPTER 4 THE IMPACT OF THE IMPLEMENTATION OF NIR ON PSC INSPECTION SYSTEM

Since being introduced in 2011, the Paris MoU continuously amended the related regulations and policies to improve the efficiency of the NIR. In this chapter, a comprehensive analysis is conducted to test the influence of the implementation of NIR on the PSC inspection results. From several different perspectives, a comparative analysis between the 'Pre-NIR' period and 'Post-NIR' period is conducted, and the significance of the NIR is revealed to demonstrate its ability to transform and modernise the PSC inspection system in the Europe region.

4.1 INTRODUCTION

PSC programs, which render port authorities the ability to inspect the foreign vessels in their own ports, have turned to port inspections to prevent shipping accidents and other risks from occurring in their legal waters. In recent years, it is regarded as the last line of defence in dealing with substandard vessels.

In 2011, the much-anticipated NIR was finally launched on January 1st after many years of preparation. It was viewed as the most significant change that transforms and modernises the PSC system in recent years. Compared to the old system that was based on the agreement from 30 years ago, NIR introduced a radical change. The change was necessary to bring the Paris MoU in line again with global maritime developments, introduction of new IMO instruments and a better-balanced method of targeting and inspection of ships. The main objective during the development has been to reward quality shipping and to intensify control and sanctions on ships with poor performance.

The new regime introduces a major departure from the "25% inspection commitment" and 6-month inspection intervals, which overburdened the shipping industry and PSC authorities with inspections. When the criteria are met, quality ships will be rewarded with a "low risk ship" status and the inspection interval may be up to 36 months. Even "standard risk ships" benefit from the new system extending inspection intervals to up to 12 months. New to the system is that companies are now also monitored for performance, based on the inspection history of their ships.

To balance the system, more resources will be directed to those ships with poor safety records, the "high risk ships". These ships are subject to mandatory expanded inspections every 6 months when they call at a Paris MoU port. A complex system of risk calculations, targeting and recording of inspections is supported by the new database “THETIS”, hosted and managed by EMSA in Lisbon. Results of inspections, currently detained ships and banned ships are now displayed directly from THETIS on the Paris MoU web site.

It should be understood that substandard ships would no longer be tolerated in the region and with the new refusal of access measures in place, repeated offenders will be “banned” from our ports. This has happened to a substantial number of vessels already, some of which have been recycled in the meantime. Others choose to find new areas to operate, endangering the lives of the seafarers on board and constituting a risk for the environment.

As a risk-based targeting mechanism, NIR rewards quality shipping with a reduced inspection burden and concentrates efforts on high-risk vessels. Making use of not only the performance of the flag state and the RO, but also the performance of the ISM Company for calculating the ship risk profile, it is expected to be a comprehensive regime ensuring the maritime safety and preventing illegal actions of ship owners.

In order to figure out whether the implementation of NIR truly transforms the PSC system and brings significant influence on the inspection results, a comparative analysis between the ‘Pre-NIR’ period and ‘Post-NIR’ period is conducted in this chapter. The key performance indicators (KPI) provided by the annual reports of the Paris MoU from 2005 to 2016 are utilized to analyse the influence of NIR from a macro-level perspective. In addition, with the help of two BN models, the micro-level changes that NIR brings to the PSC inspection system are revealed from different angles, e.g. influence of company performance, the sensitivity to detention, and the priority change of risk factors (vessel-related or inspection-related).

4.2 MACRO-LEVEL ANALYSIS - THE INFLUENCE OF NIR ON PSC INSPECTION

In this section, a macro-level analysis is conducted to describe the impact of the implementation of NIR. The Paris MoU displays the detailed information and KPIs related to PSC inspection results on its website, which provides the data source for the analysis. Through the data collection process, the facts & figures of PSC inspections in 2005-2016 are summarized and listed from annual reports of the Paris MoU, including number of inspections, number of inspected vessels, number of deficiencies, number of detainable deficiencies, number of detentions, and refusal access of vessels. The statistics are specific to different vessel types. Each category corresponds to an important aspect to judge the efficiency of the NIR and represents a criterion to estimate the overall quality and safe condition of inspected vessels. Understanding the changes of PSC inspections in these aspects is essential for us to clarify the macro-level influence brought by NIR on the PSC inspection system. Unlike the BN models developed in Chapter 3, the statistics collected from the Paris MoU focus on all vessel types, not the bulk carriers only.

4.2.1 General analysis

4.2.1.1 Facts & Figures

To start our research, the facts and statistics about PSC inspections are collected in chronological order from 2005 to 2016, containing various aspects of the previous and current conditions of the PSC inspections in recent decades. The number of inspections, the individual vessels inspected, the number of deficiencies, the detainable deficiencies, the number of detentions, and the number of access refusals each year are all recorded in the database and considered in this study. The changes in these aspects are important signals representing the influence brought by NIR, because these are all important KPIs in the PSC inspection system, as stated in Paris MoU official statements. Table 4.1 lists these KPIs value derived from Paris MoU annual reports in 2005-2016. Because of the lack of statistics, the detainable deficiencies in 2005 and 2006 are vacant.

Table 4.1 The facts of PSC inspection from 2015 to 2016

Year	Inspections	Individual vessels	Deficiencies	Detainable deficiencies	Detentions	Refusal of access to ships
2016	17840	15234	41857	3769	683	20
2015	17877	15225	41777	3513	610	11
2014	18477	15386	46224	3155	623	21
2013	17687	14108	49074	3231	668	29
2012	18308	14646	49261	2882	669	14
2011	19058	15268	50738	3080	688	20
2010	24058	14762	64698	3866	790	6
2009	24186	14753	71911	5451	1059	13
2008	24647	15237	83751	6280	1220	19
2007	22877	14182	74713	6434	1250	14
2006	21566	13417	66142	-	1174	14
2005	21302	13024	62434	-	994	28

(Source: Paris MoU)

It is worth noting that some of the statistics in Table 4.1 may not suitable to use for analysis directly. For example, the number of deficiencies per year experienced a huge decline (e.g. 64698 in 2010 and 50738 in 2011) when NIR was implemented in 2011, however, at the same time, the inspections per year also reduced largely from 24058 to 19058. If simply drawing the conclusion that the PSC inspection system improved a lot because of the decline in the number of deficiencies, the analysis would be one-sided as the decline in the number of inspections is a signal of a negative effect on the PSC inspection system. The mutual contradiction of the facts hinders our analysis. Hence, in order to make the conclusions reasonable, some KPIs in Table 4.1 need to be adjusted to help the research.

To support the analysis, deficiency rate, average inspected time per vessel, detainable deficiency rate, detention rate and refusal rate are calculated to replace some KPIs in table 4.1, like the number of deficiencies, the number of detainable deficiencies, the number of detentions, and the number of access refusals. Table 4.2 presents the calculated results.

Table 4.2 The results of inspection-related rates in 2005-2016

Year	Deficiency rate	Average inspected time per vessel	Detainable deficiency rate	Detention rate	Refusal rate
2016	2.346	1.171	0.211	3.83%	0.11%
2015	2.337	1.174	0.197	3.41%	0.06%
2014	2.502	1.201	0.171	3.37%	0.11%
2013	2.775	1.254	0.183	3.78%	0.16%
2012	2.691	1.250	0.157	3.65%	0.08%
2011	2.662	1.248	0.162	3.61%	0.10%
2010	2.689	1.630	0.161	3.28%	0.02%
2009	2.973	1.639	0.225	4.38%	0.05%
2008	3.398	1.618	0.255	4.95%	0.08%
2007	3.266	1.613	0.281	5.46%	0.06%
2006	3.067	1.607	/	5.44%	0.06%
2005	2.931	1.636	/	4.67%	0.13%

(Source: Author)

Based on the statistics in Table 4.1 and 4.2, the macro-level analysis is carried out focusing on these aspects, which is presented in the following sections.

4.2.1.2 Change in the number of inspections & individual vessels

According to the Table 4.1, the number of inspections & inspected vessels per year are picked up and used to form the column chart showed in Figure 4.1.

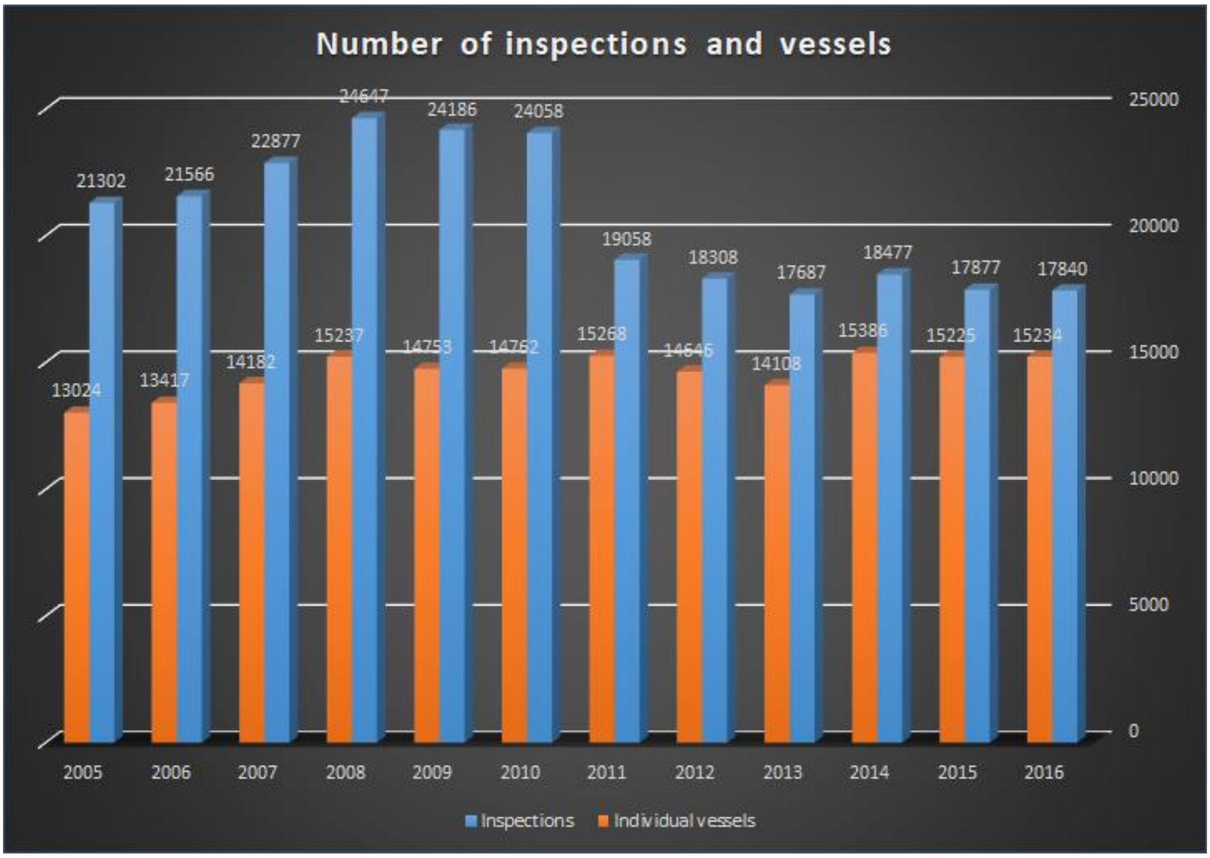

Figure 4.1 Number of inspections and individual vessels in 2005-2016

(Source: Author)

From Figure 4.1, several changes related to the two KPIs because of the implementation of NIR are revealed.

1) It is obvious to find that there was a decrease in the number of inspections, but an increase in the number of individual inspected vessels in 2011 when NIR was implemented.

The phenomenon is one of the influences that NIR brings to us. In the previous inspection system, each member state of the Paris MoU would inspect 25% of the individual vessels calling at their ports, which is called national commitment. However, under new regime, each member only inspects the vessels visiting the ports and anchorages in the Paris MoU region. The transformation from national commitment to regional commitment results in the change of targeting of inspected vessels. Since 2011, the annual inspection target for each member state is based on ship movement data rather than individual ship calls and dedicated quality shipping is rewarded with longer inspection intervals. Consequently, the number of inspections executed per year dropped.

2) From 2011, the number of inspections and individual inspected vessels continued to drop, except 2014, when both indicators increased slightly.

Under the new inspection system, the recorded ships will be categorized into three risk types: low risk ship, standard risk ship, and high-risk ship. For different types of vessels, the inspection intervals are different. HRS has a 5 to 6 months interval, SRS has a 10 to 12 months interval, while LRS has a 24 to 36 month interval. In other words, the inspection on HRS is semi-annual, while it is annually for SRS and 2-3 years for LRS. Hence, when it comes to 2014, the third year since the NIR was implemented, a large number of LRS needed to be inspected, indicating an increase in both the number of inspections and individual inspected vessels.

Meanwhile, because SRP is re-calculated on a daily basis, when an SRS or HRS is inspected next time, it may be upgraded to a safer level, thus leading to a decreasing trend in both indicators.

3) Since NIR was implemented, both the number of inspections and the inspected vessels per year remain stable compared to the former inspection system.

After the implementation of NIR, the number of inspections per year was around 18,000, except the first year of implementation that had about 19,000. Meanwhile, the number of inspected vessels per year has bounced around in a tight range near 15,000. All these signs indicated that the implementation of NIR made the PSC inspection system more stable than ever. Additionally, the fewer inspections carried out per year reduced the workload and the consumed resources of port authorities

4.2.1.3 Change in deficiency rate and detainable deficiency rate

Figure 4.2 presents a column chart for the change of deficiency rate and detainable deficiency rate from 2005 to 2016. Here deficiency rate refers to the average number of deficiencies per inspection; detainable deficiency rate goes the same. The trend in the figure reveals several changes that NIR brings to the inspection system.

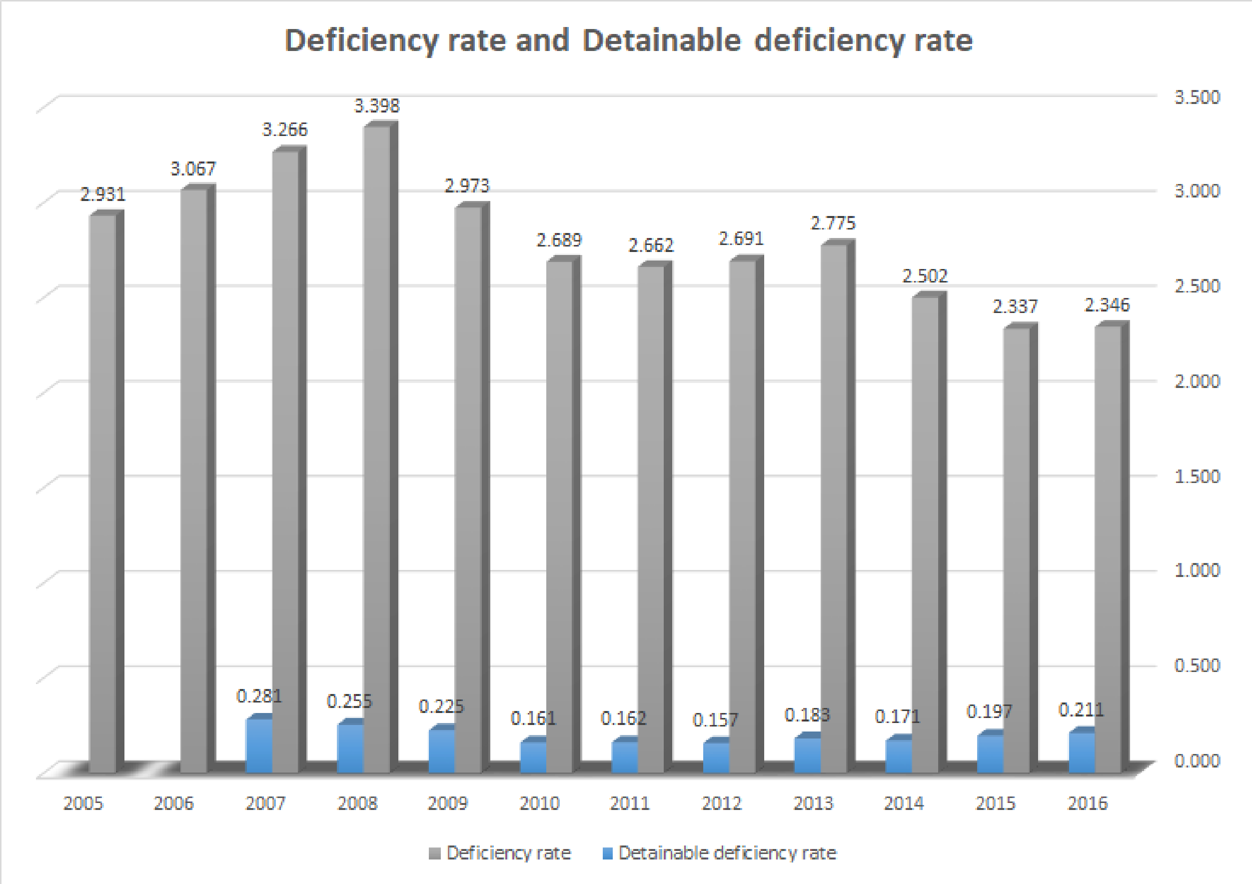

Figure 4.2 Deficiency rate and detainable deficiency rate in 2005-2016

(Source: Author)

1) The introduction of NIR significantly reduced the deficiency rate and detainable deficiency rate of vessels inspected under the Paris MoU inspection system. (Year 2010 is a special case that will not be considered)

Although the number of inspections and deficiencies decreased simultaneously since the NIR was implemented, the descending trends of deficiency rate and detainable deficiency rate in Figure 4.2 reveals the decline in the number of deficiencies and detainable deficiencies (positive effect of NIR) was greater than the number of inspections (negative effect), which demonstrate the effectiveness and applicability of the NIR.

For the year 2010, the Paris MoU conducted a Concentrated Inspection Campaign (CIC) on tanker damage stability that came into effect from 1st September to 30th November. This activity prompted every tanker (e.g. oil, gas, chemical) operator to improve their vessels' quality and the relevant documentation to comply with applicable regulations. Hence, 2010 was a special year that had the lowest deficiency rate before 2011, in spite of the NIR has not been implemented.

2) Since NIR was implemented, the deficiency rate maintained a downward trend, from 2.662 in 2011 to 2.346 in 2016, especially in 2014, where there was a huge decline. On the contrary, the detainable deficiency rate experienced a slightly increase.

The contradictory trends of deficiency rate and detainable deficiency rate form an interesting situation. On the one hand, the continuous improvements of NIR urged the ship owners to pay more attention to the quality of their vessels, thus resulting in a descending trend of deficiency rate. For example, in 2014, 55% of the performed inspections had one or more deficiencies, and in 2013, this figure was 58%. The decline of deficiency rate reflected the improvement of the vessel quality.

However, on the other hand, the passion and motivation of ship owners weakened after the 'honeymoon' of the NIR. It will cost them a lot to maintain and repair the vessels, especially in those places that may cause detainable deficiencies. Hence, the pathology of gambling makes them unwilling to maintain the quality of vessels and hope to pass the inspection by luck. The changes in psychology may be an important reason for the increase in the detainable deficiency rate, and such mentality will be explained in detail in the next chapter.

4.2.1.4 Change on detention rate

As the most intuitive KPI, detention rate reflects the overall inspection situation over a period. Figure 4.3 illustrates the variation of the detention rate in the last decade, from 2005 to 2016.

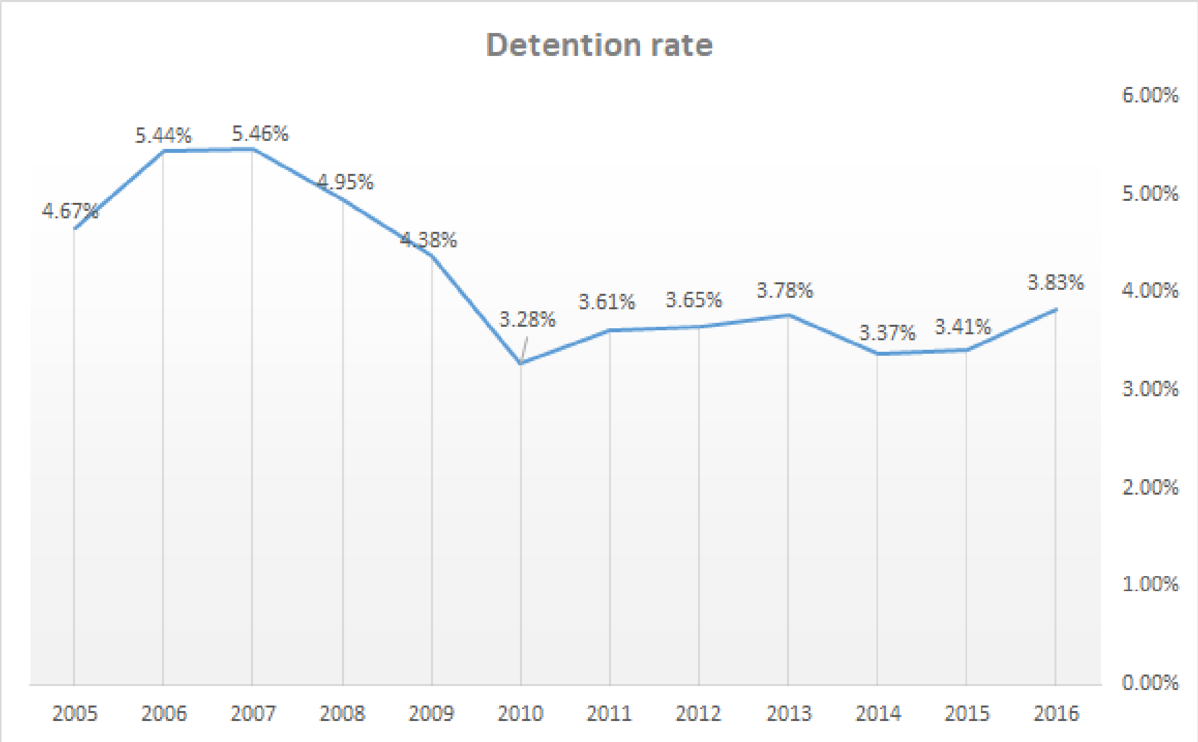

Figure 4.3 Trend of detention rate in 2005-2016

(Source: Author)

1) Overall, the detention rate after 2011 is lower and more stable compared to the period before NIR.

Although in 2010, the detention rate declined sharply and reached the lowest point in the past decade, the overall detention rate before and after the implementation NIR is widely different, which is demonstrated as follows:

Detention rate from 2011-2016: 6487/138636=4.68%

Detention rate from 2011-2016: 3941/109247=3.61%

The improvement on detention rate: (4.68%-3.61%)/4.68%= 22.86%

The calculation above shows that the detention rate dropped 22.86% since NIR was implemented. It is obvious that the introduction of NIR indeed improved the operation of the PSC inspection system and stimulated the ship owners to spend more on the maintenance of the quality of their vessels.

Meanwhile, the range of fluctuation of detention rate after 2011 is less than 0.5%, far lower than the 2.18% range in 2005-2010, demonstrating the PSC inspection system is currently running healthily and stable.

2) Before the implementation of NIR, the detention rate dropped to 3.28%, the lowest point until now.

This interesting phenomenon can be explained by the following reasons.

First, as mentioned before, the Paris MoU conducted a Concentrated Inspection Campaign (CIC) on tanker damage stability that came into effect from 1st September to 30th November in 2010. This activity prompted every tanker (e.g. oil, gas, chemical) operator to improve their vessels' quality and the relevant documentation to comply with applicable regulations. Hence, the overall quality of vessel types was much better.

Second, although NIR was implemented in 2011, it was announced by the Paris MoU in 2009 that a new and more rigid inspection regime would come into force in 2011. In order to better adapt to the new system when it came out, most ship owners chose to improve the quality of their vessels as much as possible to avoid severe punishment if NIR was implemented later. Hence, the overall quality of the vessels in maritime transportation improved, resulting in a lower detention rate reflected by the PSC inspection system.

3) Year 2014 witnessed a relatively huge decrease in the detention rate. However, the detention rate increased a lot in 2016, for the first time since 2013.

There are two interesting points after the implementation of NIR. One is 2014, when there was an increase in the number of inspections. The majority of the growing segment was LRS, leading to a decreasing tendency of detention rate.

The other is 2016, when the detention rate reached the peak value since the introduction of the NIR in 2011, along with the highest value of detainable deficiency rate. Under the rising economic pressures, some ship owners decided to choose to cut corners in areas where it is possible to reduce the operating costs of their vessels. Cooperating with some shipping companies, they made the deliberate choices to operate sub-standard vessels, mainly because the costs of running a 'bona fide operation' outweigh the risk of being detained and rectifying deficiencies. As the ship operators are getting more and more familiar with the NIR, it is predictable that the detention rate may remain at a relatively high level compared with the first two or three years. It is noteworthy that the Paris MoU increases the penalties to ensure the sub-standard shipping will not flourish, for example, the number of banned vessels in recent years.

4.2.1.5 Other KPIs

Besides the KPIs mentioned above, the average number of inspections per ship and the refusal rate per ship are also indicators may reflecting the influence of NIR.

Figure 4.4 and Figure 4.5 use the line charts to describe the trend of average number of inspections per ship and the refusal rate. Through the investigation on the charts, the influence of NIR on these two aspects is revealed below:

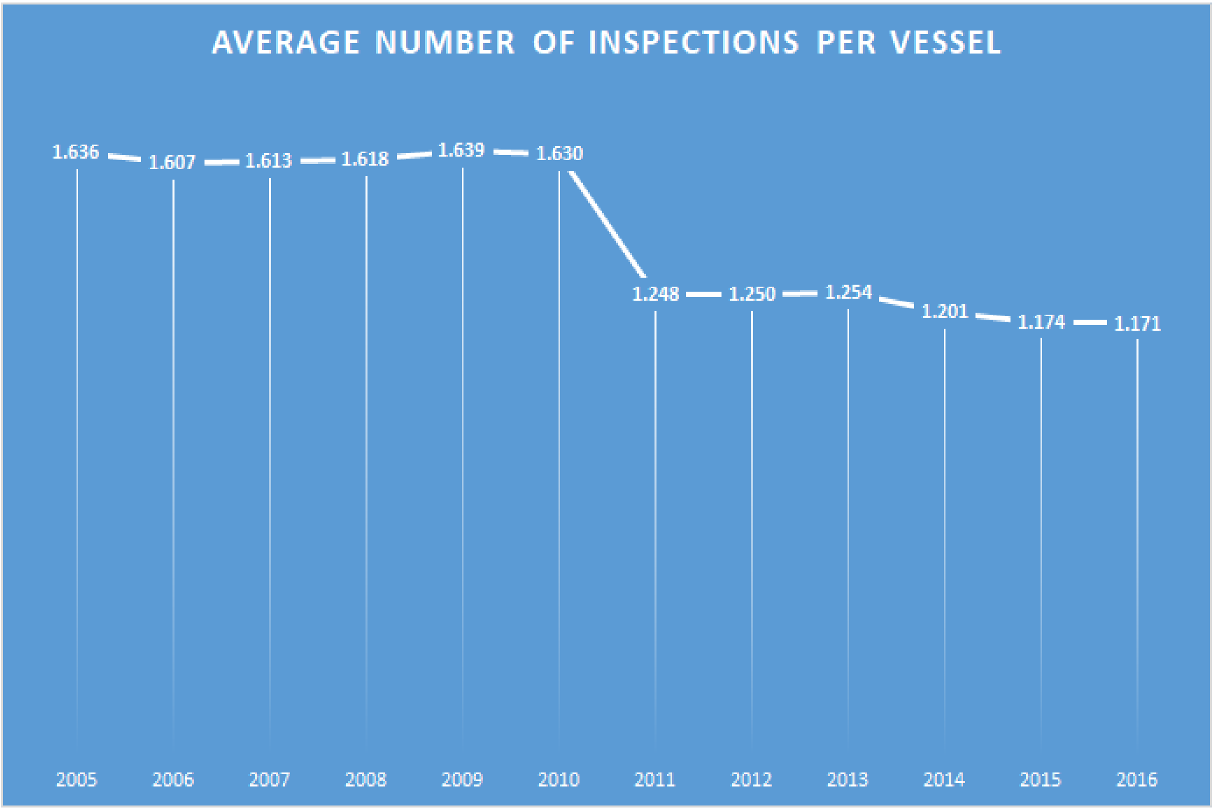

Figure 4.4 The trends of average number of inspections/vessel

(Source: Author)

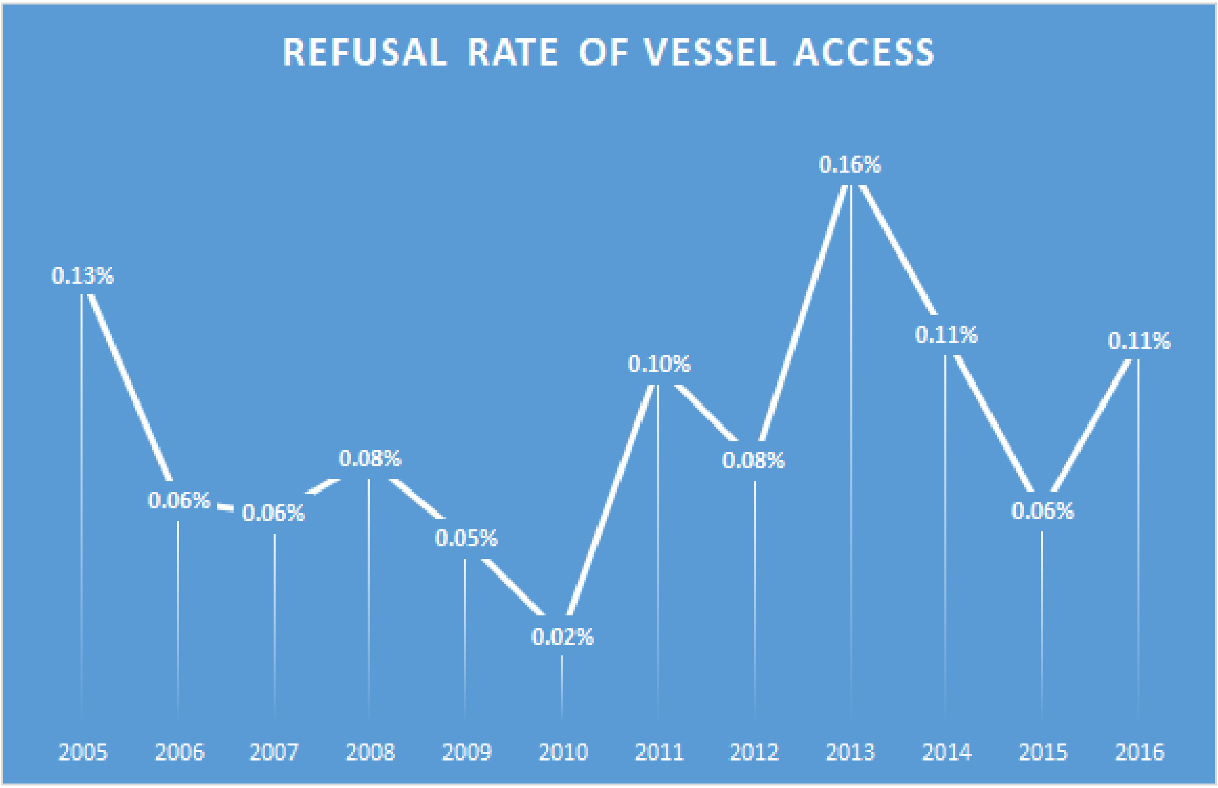

Figure 4.5 The trends of refusal rate of vessel access

(Source: Author)

1) The implementation of NIR significantly reduced the burden on the ship owners (from 1.6 inspections/year to 1.2 inspections/year).

The number of inspections per vessel per year can represent the inspection burden on the ship owners. A higher value of this indicator means that the vessel needs to be subjected to more inspections per year, increasing the burden on its ship owner.

Since NIR was implemented, this indicator dropped from 1.6 to approximate 1.2. The huge decrease on this indicator is a signal that the cost to ship owners of preparing for PSC inspections reduced a lot, representing a positive effect brought by NIR to ship owners.

2) NIR has no influence on the refusal rate of vessel access.

According to the statistics, the access refusal rate of vessels was the only indicator that NIR had no influence on in the past decade. One possible reason for this is that the refusal of a vessel is a rare event in PSC inspections that may only occur 10 to 20 times per year. This kind of rare event is hard to control for port authorities, because the sampling size is too small.

4.2.2 Influence of NIR on different vessel types

In section 4.2.1, the statistics reveals that every year over 10,000 individual vessels are inspected at the ports within the region of the Paris MoU, including bulk carrier, chemical tanker, combination carrier, etc. Different vessel types have different inspection performance, reflecting the overall quality of the vessels. Since the implementation of NIR, different vessel types adopted different measures to cope with the new inspection system and regulations, resulting in different changes in the performance during the inspections. In this section, to figure out the influence of NIR on vessel types, an analysis on the variation of some important KPIs is carried out. The results revealed clarify the impact degree of different vessel types.

Due to the fact that more than 20 types of vessels are inspected at ports, it is difficult and impossible to analyse all of them. Hence, only the types having more than 1,000 inspections every year are selected, including the following five vessel types: general cargo vessel, container, bulk carrier, chemical tanker and oil tanker.

4.2.2.1 Number of inspections

As the most direct indicator, the changes in the number of inspections brings the most remarkable perception on the influence of NIR. Figure 4.6 illustrates the trend of number of inspections of different vessel types from 2005-2016.

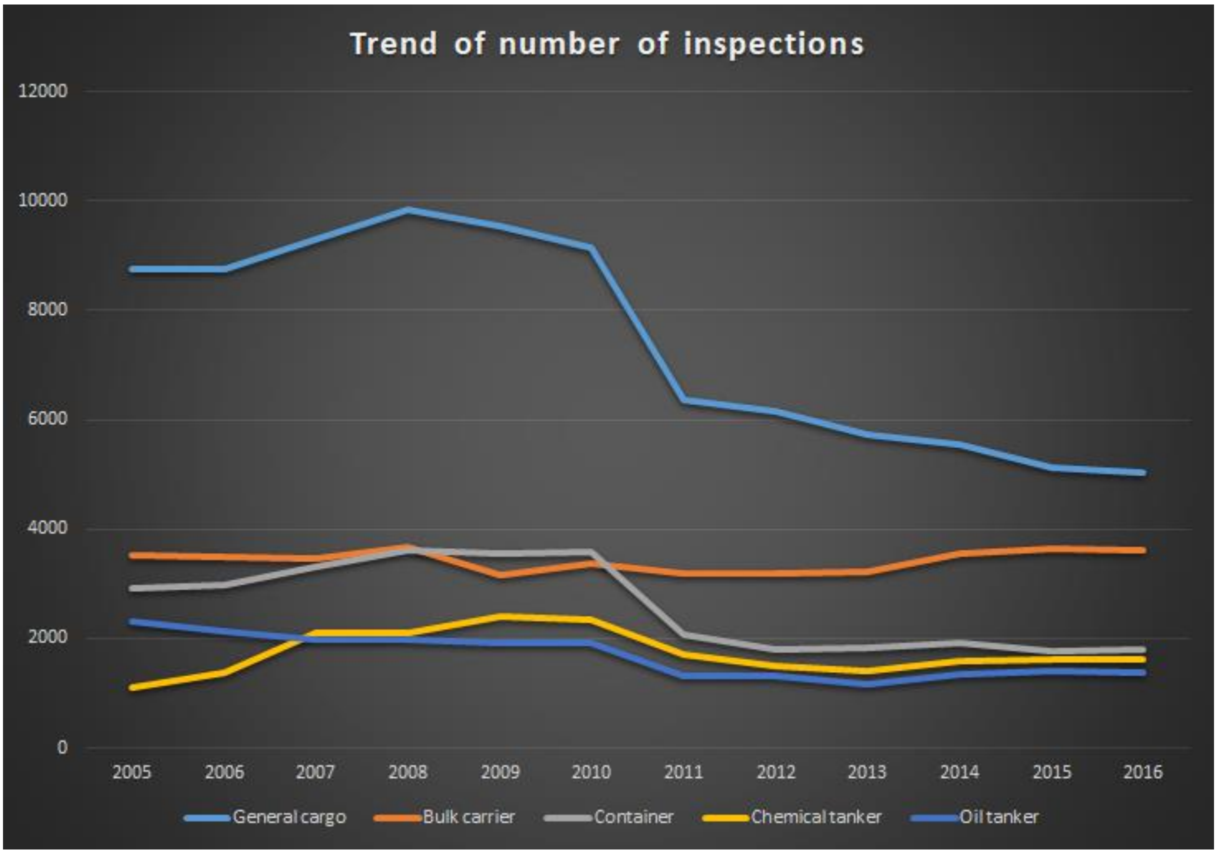

Figure 4.6 Number of inspections of different vessel types in 2005-2016

(Source: Author)

1) The inspections on general cargo vessels were far more than other vessel types, however, the gap narrowed since the implementation of NIR. In addition, the gap has become smaller and smaller over the last decade. (e.g. in 2008, the inspections on general cargo vessels were 9,851, the second was bulk carrier with 3,684; in 2016, the inspections on general cargo vessels and bulk carriers were 5,048 and 3,619, respectively.)

2) When NIR was implemented in 2011, most of the vessel types experienced a huge drop in the number of inspections, except bulk carriers, which remained at almost the same number of inspections.

3) After 2011, the inspections on general cargo vessels maintain a momentum of decline, while other vessel types (bulk carrier, container, chemical tanker and oil tanker) remained stable until 2016.

Overall, the implementation of NIR reduced the number of inspections of most vessel types, and kept this number at a steady level.

4.2.2.2 The percentage of inspections with deficiencies

Among the inspections performed, some inspections recorded one or more deficiencies, others refer to the vessels without faults. Although having deficiencies does not mean the inspected vessels are sub-standard, the percentage of inspections with deficiencies is still an important indicator to measure the overall quality of the inspected vessels. Figure 4.7 presents this KPI of different vessel types. To simplify the work, this KPI is referred as 'PID'.

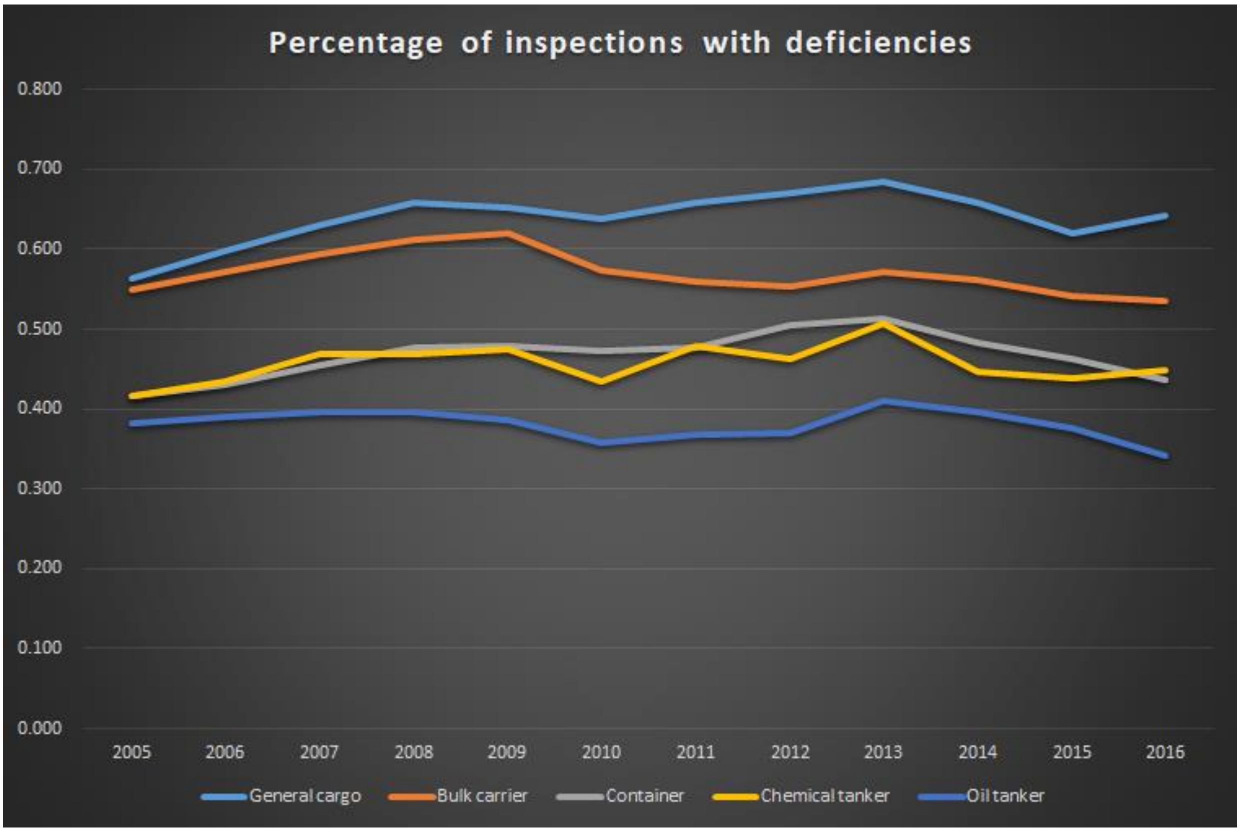

Figure 4.7 Percentage of inspections with deficiencies of different vessel types in 2005-2016

(Source: Author)

1) When NIR was implemented in 2011, the PID of most vessel types experienced a more or less growing tendency, except bulk carrier, indicating bulk carrier owners adapted to the new regulations better.

2) In 2013, the PID of all vessel types reached the peak value at the same time. Subsequently, the values began to drop, revealing more efforts are made by the ship owners to maintain the vessel quality from 2014.

3) In 2016, the PID of the general cargo vessels and the chemical tankers increased, especially the general cargo vessel, mainly because the ship owners of these vessels took risks to pass the inspection at the lowest cost due to the economic pressures. (The detailed explanation can be found in 5.3.1.4)

Figure 5.7 tells us that the deficiency rate of most vessel types did not change much, except bulk carriers, which had a lower deficiency rate compared to the 'Pre-NIR' period.

4.2.2.3 The detention rate

The trends of detention rates of different vessel types, as well as the average detention rate, are depicted in the Figure 4.8. Through the comparison between the different curves in the following figure, several conclusions can be made (the average detention rate is referred as 'ADR', presented in a black line).

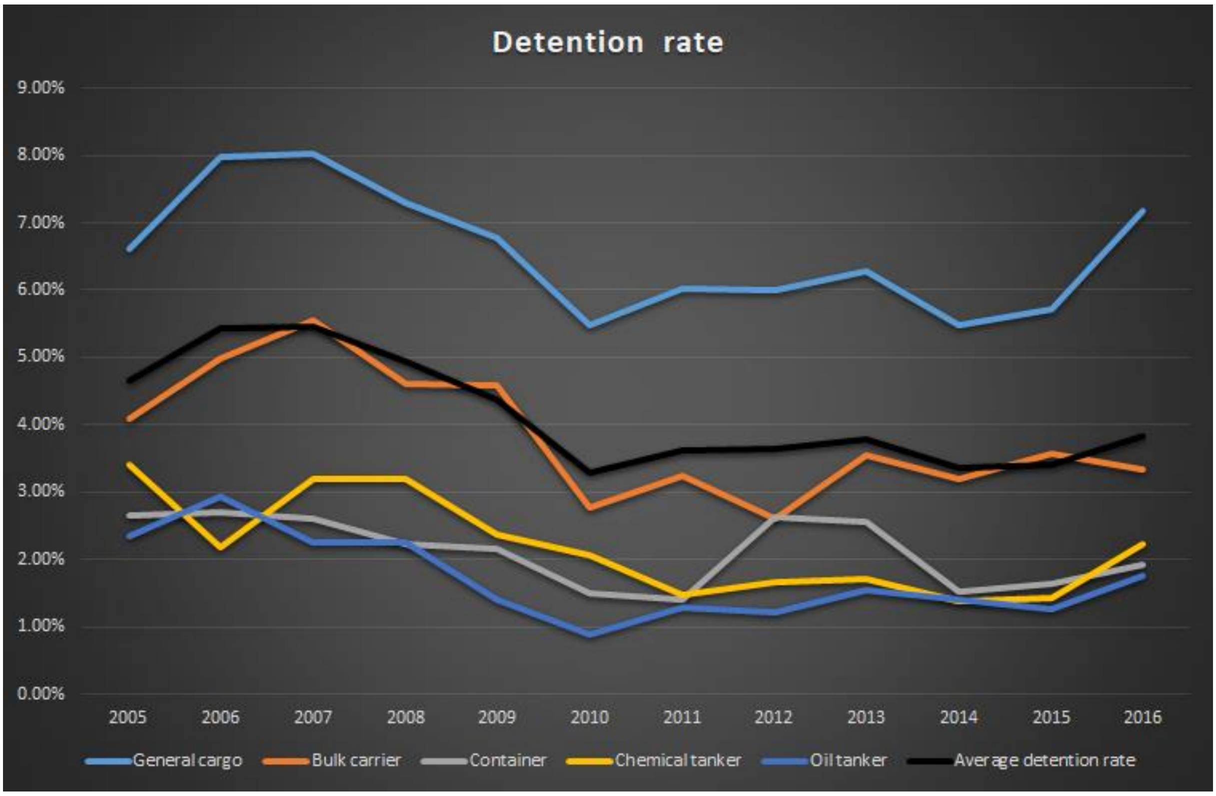

Figure 4.8 Detention rate of different vessel types in 2005-2016

(Source: Author)

1) In general, the detention rate of these vessel types all dropped, indicating the positive influence on detention rate of NIR suited for the major vessel types in the PSC inspection system.

2) The detention rate of bulk carrier is mostly the same with the ADR, indicating the bulk carrier can be used to represent the inspection system. (This is part of the reason that bulk carriers are selected as the target vessel type.)

3) The detention rate of general cargo vessel is much higher than ADR, revealing general cargo vessels as the most dangerous and risky vessel type under NIR.

4) Container vessels, chemical tankers and oil tankers have better performance and lower detention rates.

5) After 2011, the detention rates of different vessel types remained stable in general, except 2016, when the situation became worse and the detention rates increased.

4.2.3 Summary

In this part, the influence brought by NIR is clarified from the perspective of macro-level analysis. As a summary, the influence is classified into three types: positive influence, negative influence, and no influence. Only the influence related to trends is considered, meaning those special cases in a particular year are not taken into account in this part.

Positive influence

1) From 2011, the number of inspections and individual inspected vessels continued to drop, except 2014, when both indicators increased slightly.

2) Since NIR was implemented, both the number of inspections and the inspected vessels per year remained stable compared to the former inspection system.

3) The introduction of NIR significantly reduced the deficiency rate and detainable deficiency rate in the Paris MoU inspection system.

4) Since NIR was implemented, the deficiency rate maintained a downward trend, from 2.662 in 2011 to 2.346 in 2016, especially in 2014, when there was a huge decline.

5) The detention rate after 2011 was lower and more stable compared to the period before NIR.

6) The implementation of NIR significantly reduced the burden on the ship owners (from 1.6 inspections/year to 1.2 inspections/year).

7) The implementation of NIR reduced the number of inspections of most vessel types, and kept this number at a steady level.

8) The detention rate of all vessel types dropped, indicating the positive influence on detention rate of NIR suited for the major vessel types in the PSC inspection system.

Negative influence

1) The detainable deficiency rate experienced a slightly increased trend after the implementation of NIR.

No influence

1) NIR has no influence on the access refusal rate of vessels.

2) The deficiency rate of major vessel types did not change much, except bulk carriers, which had a lower deficiency rate compared to the 'Pre-NIR' period.

In summary, the implementation of NIR is a positive action from the macro-level perspective. Most of the influence brought by NIR is beneficial for the management of port authorities and maritime safety.

4.3 MICRO-LEVEL ANALYSIS - THE INFLUENCE OF NIR ON PSC INSPECTION

To fulfil the study, a micro-level analysis of the NIR influence on PSC inspection is reviewed in this section. The two proposed BN models, 'Pre-NIR' and 'Post-NIR', provide the opportunity for us to carry out this part of research. As mentioned in Chapter 3, the PSC BN model can estimate the detention rate, reveal the inner relationships between different risk factors, and identify the degree of importance of individual variables. Due to the different periods that two BNs focus on, the results obtained from two BNs are different, reflecting the micro-level changes brought about by the implementation of NIR.

The analysis is conducted from the following perspectives, including 1) the comparison of influence degree of risk factors; 2) Company performance impact; 3) Prior probability change; 4) the role of different factor groups. Each aspect is one of the results and implications that can be obtained from BN, and represents the possible changes brought by the implementation of NIR. Through the comparison of the information of these aspects in two BNs, the micro-level influence of NIR on the PSC inspection system will be clear.

Figuring out the evolution of NIR in micro-level aspects is essential to understand the essence of NIR, as well as its intrinsic effects.

4.3.1 Sensitivity to detention -The influence degree of risk factors under different periods

According to previous analysis on mutual information, only the nodes having strong relationships with 'detention' are selected to conduct the scenario simulations and TRI calculation. In section 3.3.6 and section 3.4.6, the selected nodes of two models are presented. Each model picks six nodes to do the comparison.

Pre-NIR: Inspection group, Vessel group, Number of inspections, Type of inspections, Vessel flag, RO

Post-NIR: Inspection group, Vessel group, Number of inspections, Type of inspection, Vessel age, Company performance

For different periods, the selected nodes and the results of sensitivity analysis (TRI) are different, revealing the influence degree of risk factors on inspection results changes over time. Due to the fact that the value of TRI represents the degree of importance of the nodes, it is necessary to compare the results of two BNs to clarify the changes caused by NIR in this aspect.

Table 4.3 and Table 4.4 presents the results of sensitivity analysis from both 'Pre-NIR' BN and 'Post-NIR' BN as proposed in Chapter 3.

Table 4.3 Results of sensitivity analysis (Pre-NIR)

Sensitivity to 'detention' （Pre-NIR）			
Node	**Mutual Info**	**Percent (%)**	**TRI (%)**
Inspection group	0.09654	36.4	17.34
Number of deficiencies	0.09386	35.3	16.98
Type of inspection	0.01464	5.51	7.27
Vessel group	0.00140	0.527	4.59
RO	0.00025	0.0933	2.86
Vessel flag	0.00025	0.0929	0.3

(Source: Author)

Table 4.4 Results of sensitivity analysis (Post-NIR)

Sensitivity to 'detention' (Post-NIR)			
Node	**Mutual Info**	**Percent (%)**	**TRI (%)**
Inspection group	0.06135	29.7	15.87
Number of deficiencies	0.04891	23.7	17.48
Vessel group	0.03622	17.5	7.17
Company Performance	0.02659	12.9	6
Vessel age	0.00638	3.09	3.2
Type of inspection	0.00579	2.8	2.24

(Source: Author)

Through the comparison between the results of two periods, several findings are concluded with respect to the influence of NIR.

1) In general, the stronger relationship with 'detention', the greater influence on the inspection results it will be.

2) Since NIR was implemented, the relationships between risk factors and 'detention' have become closer and stronger. This change is reflected in the percentage of mutual information (PMI). In 'Pre-NIR' model, the gap of the PMI value between the first two factors and other factors is huge (35.3% for 'number of deficiencies', 5.51% for 'type of inspection', and other factors lower than 1%), which is abnormal for the inspection system. As a comparison, the gap between different risk factors is narrowed since the implementation of NIR (29.7%, 23.7%, 17.5%, 12.9% respectively), indicating the influence of different risk factors on inspection results are becoming closer under the new situations.

In a word, the implementation of NIR provides a healthier and more reasonable inspection system for port authorities. Within the system, every risk factor is endowed with scientific influence on the inspection results.

3) After the implementation of NIR, the number of deficiencies becomes the most influential factor in PSC inspection.

4) Vessel group, as well as the vessel age, are paid more attention since the implementation of NIR.

5) The newly added factor, company performance, indeed influences the inspection results to some extent. Although not as influential as ‘number of deficiencies’, it is still one of the factors that should be of concern to port authorities.

6) Before the implementation of NIR, inspection type was one of the most influential factors. However, after 2011, the TRI value of inspection type drops from 7.27% to 2.24%, indicating it is no longer as important as it used be.

7) Compared to other factors, the relationships with ‘detention’ of RO and vessel flag are relatively weak, hence not listed in the table after the implementation of NIR.

4.3.2 Company performance impact

As a newly added factor in the PSC inspection system, company performance plays an important role when calculating the SRP of the vessels. It is viewed as one of the significant improvements and changes on the inspection system stated by many PSCOs and members of the Paris MoU. The analysis of degree of importance above has already proved that company performance indeed has an important effect on the occurrence probability of detention, and even within the range of the most influential factors.

In this section, the effect of company performance is further clarified. The sensitivity analysis with respect to the given states of company performance is shown is Table 4.5, including the detention rates and changes rate to the normal condition.

Table 4.5 Effect of company performance

High	**Medium**	**Low**	**Very low**	**Detention rate**	**Changes rate**
-	-	-	-	3.25%	
100%	0	0	0	1.49%	-54.15%
0	100%	0	0	1.32%	-59.38%
0	0	100%	0	9.17%	+182.15%
0	0	0	100%	14.9%	+358.46%

(Source: Author)

In this table, ‘-‘means the reduction of detention rate, ‘+’ means the increment of detention rate.

1) If the performance of the management company is poor, the changes in the detention rate will be huge, up to 182.15% (low), and even 358.46% (very low).

2) On the contrary, a high or medium performance ISM company will reduce the detention rate to some extent, and there is no big difference between high company performance and medium company performance.

3) The attitudes of port authorities towards vessels under the management of low and very low shipping companies are rigorous, much more than the benefits gained from selecting a high/medium management company.

4) The huge change in the inspection results of different performance levels reflects company performance is viewed as a high risk factor from the perspective of port authorities, demonstrating the fact that an ISM company is no longer beyond the control of the PSC inspection system.

4.3.3 Prior probability change

Another change lies in the prior probabilities of risk factors before and after the implementation of NIR. The investigation on this aspect can help reveal the change on actions taken by port authorities and ship owners under NIR, respectively. The involved factors are vessel age, vessel flag, inspection type, and port of inspection. Table 4.6 lists the related information. Canada and Greece in the Post-NIR model are not considered, because they are not within the range of the states of ‘port of inspection’ in the Pre-NIR model. Hence, a normalization on the other seven countries after the implementation of NIR is conducted and presented in the table.

Table 4.6 Comparison of prior probability before and after NIR

Vessel flag							
	Black (High)	Black	Grey	White			
Pre-NIR	0.0103	0.2218	0.0671	0.7008			
Post-NIR	0.0077	0.0109	0.0150	0.9664			
Vessel age							
	0to5Years	5to10Years	10to15Years	15to20Years	Over20Years		
Pre-NIR	0.1340	0.1392	0.1519	0.0752	0.4998		
Post-NIR	0.2633	0.3884	0.1876	0.1051	0.0556		
Port of inspection							
	Belgium	France	Germany	Italy	Netherlands	Spain	UK
Pre-NIR	0.1297	0.1360	0.0866	0.1564	0.1243	0.2356	0.1315
Post-NIR	0.0806	0.1057	0.1027	0.1593	0.1975	0.2072	0.1470
Inspection type							
	Initial	More detailed	Expanded				
Pre-NIR	0.2814	0.3668	0.3518				
Post-NIR	0.3447	0.4319	0.2234				

(Source: Author)

It is obvious to find there are huge changes on the prior probabilities of these aspects, indicating various trends on the inspections.

1) The flag performance of inspected vessels improves a lot and almost all the inspected vessels have a white list flag.

After 2011, more and more ship owners select flag states that are listed on the white list of the Paris MoU (from 0.7008 to 0.9664). On the contrary, the percentage of selecting black list flag states declined sharply from 0.2218 to 0.0109, and the other two states of 'vessel flag' experience a slightly drop as well.

2) Young vessels replace the position of old vessels and become the majority part of inspected vessels.

Currently, the majority of inspected vessels are young vessels under 10 years old, occupying over 60% of the total number. This figure was only around 27% before the implementation of NIR. Meanwhile, the percentage of vessels over 20 years old drops significantly from 49.98% to 5.56%.

3) There is not much change in the port of inspection before and after the introduction of NIR.

As an unimportant risk factor, the places of inspections seem not to have been influenced by the implementation of NIR. The percentage of inspections taking place in seven major costal countries in Europe remains almost the same, except Netherlands, which had a small increase (from 12.43% to 19.75%) in this area.

4) More-detailed inspections is the preferred inspection type of port authorities.

Before NIR was implemented, port authorities executed almost the same number of more detailed inspections and expanded inspections. However, since the overall quality of vessels has improved nowadays, more and more initial and more-detailed inspections are carried out, and the percentage of expanded inspections has decreased from 35.18% to 22.34%.

4.3.4 The role of 'vessel group' and 'inspection group'

Although 'vessel group' and 'inspection group' are two dummy variables introduced to reduce the calculation work of CPTs, they actually represent the overall level of vessel-related risks and inspection-related risks. Understanding the changes of the impact degree of two factors is essential to figure out which part is more risky and which part is paid more attention compared to the former inspection system.

Table 4.7 illustrates the changes rate of two variables under different scenarios. '-'means the reduction of detention rate, '+' means the increment of detention rate.

Table 4.7 The change on 'vessel group' and 'inspection group'

Inspection	Pre-NIR	Post-NIR	Vessel	Pre-NIR	Post-NIR
Prior probability	4.52%	3.25%	Prior probability	4.52%	3.25%
Posterior probability (High)	35.70%	32.90%	Posterior probability (High)	8.87%	15.60%
Changes rate	+689.80%	+912.30%	**Changes rate**	+96.20%	+380%
Posterior probability (Low)	1.03%	1.16%	Posterior probability (Low)	4.28%	1.26%
Changes rate	-77.20%	-64.30%	**Changes rate**	-5.30%	-61.20%

(Source: Author)

The changes on this aspect are obvious, which is presented as follows.

1) Compared to the previous system, both the high inspection risk and high vessel risk vessels will have much higher chances to be detained by port authorities under the new inspection system.

2) Nowadays, vessels having low vessel-related risks will have a huge reduction in the detention rate when accepting inspections, stimulating the ship owners to be more concerned about the vessel quality.

3) No matter whether it was before or after the implementation of NIR, inspection-related risks are always the top priority of port authorities. However, vessel-related risks are no longer an indifferent part compared to inspection-related risks and have gradually become crucial to the inspection results.

4) The changes on the inspection and vessel risks demonstrate that port authorities are vigilant to all potential risks and will no longer tolerate any types of risk.

4.3.5 Summary

Based on the proposed BNs in Chapter 3, the influence of NIR from the micro-level angle is clearly understood. Similar to the findings in the macro-level analysis, some changes are positive, while other changes may not act as expected. As a summary, the intrinsic changes and influence on the PSC inspection system are categorized into three types: positive changes, negative changes, and neutral changes (Those changes do not affect the system). The summary can tell us whether the implementation of NIR is beneficial for port authorities and ship owners, even for the maritime transportation system.

Positive changes

1) Since NIR was implemented, the relationships between risk factors and the inspection results have become closer and stronger.

2) Vessel-related risk factors are paid more attention since the implementation of NIR.

3) The newly added factor, company performance, is viewed as an important risk factor that greatly affects the final inspection results. The vessels under high and medium company management are highly unlikely to be detained; on the other hand, low and very low ISM companies are on the 'black list' of all ports within the range of the Paris MoU and have greatly increased chances of detention.

4) The attitudes of port authorities towards vessels under the management of low and very low shipping companies are rigorous, much more than the benefits gained from selecting a high/medium management company for inspection.

5) The flag performance of inspected vessels improves a lot and almost all the inspected vessels have a white list flag.

6) The age of inspected vessels from 2011 is becoming younger, indicating the implementation of NIR eliminated those low quality old vessels.

7) Compared to the previous system, both the high inspection risk and high vessel risk vessels will have much higher chances to be detained by port authorities under the new inspection system.

8) Vessels having low vessel-related risks will have a huge reduction in the detention rate when accepting inspections, stimulating the ship owners to be more concerned about the vessel quality.

9) Vessel-related risks are no longer an indifferent part compared to inspection-related risks and have gradually become crucial to the inspection results.

10) Port authorities are vigilant to all potential risks and will no longer tolerate any types of risk

Neutral changes

1) After the implementation of NIR, the number of deficiencies becomes the most influential factor in PSC inspections.

2) There is not much change in the port of inspection before and after the introduction of NIR.

3) More-detailed inspections is the preferred inspection type for port authorities.

Negative changes

1) Inspection type was no longer as important as it used be.

2) The influence of RO and vessel flag greatly reduced compared to the former system.

In a word, the implementation of NIR provides a healthier and more reasonable inspection system for port authorities. Under the operation of the new regime, the vessel quality is guaranteed and the maritime safety is ensured.

CHAPTER 5 A RISK-BASED GAME MODEL FOR RATIONAL INSPECTIONS IN PORT STATE CONTROL

This chapter develops a risk-based game model via payoff matrix based on Bayesian network (BN) for guiding the ship owner and the port authority to make optimal decision strategies in PSC inspections. The results obtained from the BN model are used to help determine the crucial factors influencing the ship owner and port authority's decision on PSC inspections and their values in the game model. During this process, the risk-based PSC decision model through the innovative incorporation of game theory and BN, for the first time, takes into account the new role of International Shipping Management (ISM) (i.e. the third party) companies introduced by NIR in the game decision and exploits a rational and feasible way to analyse PSC inspection practice since NIR was implemented.

5.1 INTRODUCTION

During an inspection, PSC officers will select high-risk vessels for inspection according to the risk estimation mechanism suggested by the regional PSC organizations (Xu, et al., 2007). Since established in 1982, PSC is gradually viewed as the last safety line of defence against sub-standard vessels because it effectively restricted the appearance of the vessels not fully following the relevant safety regulations. Nevertheless, it is not perfect, leaving the holes to be addressed and new solutions to be explored. According to the PSC inspection records, every year a large number of vessels do not comply with the regulations reckoned by port authorities and fail to pass the inspections.

Generally, the ship owners need to prepare many works to make their vessels meet the requirements of PSC inspections, for example, selecting a high performance ISM company, investing capital to improve quality of vessels, and employing some experienced staff. However, because of the large amount of funds invested, especially the high maintenance cost, some ship owners do not tackle the safety loopholes of their vessels in time, leading to high risks of the vessels being detained.

Although facing huge punishment when the vessel is detained, the ship owners still gamble on the inspection, as they understand the PSC regulations well, and that it is impossible for port authorities to inspect all the vessels arriving at the port due to limited resources. Hence, on this matter, different ship owners make different decisions according to the characteristics, the circumstances, the resources owned, and the judgments on the regulations of destination ports.

From the perspective of the port authority, it costs them a lot to inspect a vessel. The limited resources, which include both the funding and the human resources (the PSC officers), restrict the amount of inspection that can be carried out. In general, the funds for the MoU are provided by each member, and the inspection costs are thus borne by them. The ports have the right to decide the resources they put into each inspection, and MoU cannot and could not charge any of them. Although having the convenience, port authorities still need to spend a lot on inspections to ensure the quality and effectiveness of them. Every day, many vessels will visit the port, and the costs are increased with higher inspection rates. Port authorities need to get further funds from some other finance channels, as well as recruit and train more related personnel to take charge of on-board inspections.

On the other hand, excessive PSC inspections may harm the competitiveness of the port and increase the burden on ship owners, leading some ship owners to turn to other destinations that may have a more relaxed inspection policy (Li, et al., 2015). Further, excessive controls, increasing delays, tied up capacities, inventory costs etc., may also be translated into costs ultimately paid by the customers (Goss, 1989).

Therefore, striking a PSC inspection balance between port authorities and ship owners requires a scientific decision for rational policymaking. While the port authorities aim at motivating ship owners to maintain their vessels at a high safety level to mitigate maritime accidents, ship owners care more about minimization of the associated costs. Such conflicts of interest therefore forms an antagonistic relationship between the two stakeholders, which is called the *inspection game*.

An inspection game is a mathematical model of a non-cooperative situation where an inspector verifies that another party, called inspectee, adheres to legal rules. The inspector wishes to deter illegal activity on the part of the inspectee and, should illegal activity nevertheless take place, detect it with the highest possible probability and as soon as possible. The inspectee may have some incentive to violate his commitments and violation, if observed, will incur punishment. Therefore, if he chooses illegal behaviour, the inspectee will wish to avoid detection with the highest possible probability. In PSC inspection, port authorities are inspectors and ship owners are inspectees.

To improve the PSC inspection system, the much-anticipated New Inspection Regime (NIR) was launched in 2011. According to Paris MoU Annual Report (2011), it is viewed as the most significant change that transforms and modernizes the PSC system in recent years. Under the new inspection system, the vessel visiting a port will be attributed a ship risk profile through an associated information system, which determines the priority of ship inspections, the intervals between the inspections of a ship and the scope of the inspections. Based on the feedback, the port authority will decide the details of the inspections, (inspection types, detention results, and detention periods). The Paris MoU hoped that the implementation of NIR could efficiently improve the performance of PSC inspection system.

It is noteworthy that an important element that helps to categorize the ship risk profiles in NIR is the performance of International Shipping Management (ISM) companies. Before the implementation of NIR, ISM companies are just third-party managers who, for a negotiated fee and with no shareholding ties with their clients, undertake the responsibility of managing vessels in which they have no financial stake (Mitroussi, 2003). They accepted ships from and managed them on behalf of ship owners without much concern on their technical soundness given that they had no responsibility on vessels' failures of passing PSC inspections. However, this practice has been changed since the NIR was introduced in 2009 and implemented in 2011 on the Paris MoU. The Paris MoU establishes a shipping company (including ISM) performance formula that takes into account detention and deficiency records of the vessels under the company's management over a period of 36 months. Based on the deficiency and detention rates, the performance of ISM companies is classified into groups of four grades: high, medium, low and very low. A list of 'ISM managers' of poor performance has been developed, consisting of the ISM companies who have shown an unwillingness or inability to comply with the international conventions on maritime safety and/or on the protection of marine environment. Once a vessel is detained, the reputation of its associated ISM will be affected, leading to an increase frequency of inspections in future.

To ensure their profits and maintain their reputation, ISM companies are putting much effort to make them adaptive to the NIR and improving their management level. Considering the vessel quality, ISM companies raise their vessel acceptance criteria to ensure the successful inspection results that the ships under their management can receive. The involvement of ISM companies obviously influences the game between port authorities and ship owners in today's PSC practice.

For port authorities, when regulating their policies under NIR, it is of vital importance to take the company performance indicator into account. However, in this research, as we only focus on the period in which the vessel is already at the port, ISM companies are considered as a factor influencing the decision-making of port authorities, because the selection and determination of ISM companies happen before the occurrence of the inspections. Therefore, quantifying the influence of company performance on inspection results becomes the major issue when analysing the PSC inspection game under NIR in this research. Further research may consider ISM companies as a player in the inspection game if the time range of the game is widened.

This chapter aims at developing a risk-based game model based on Bayesian network (BN) to determine the optimal inspection strategy of a port authority under different circumstances after the implementation of NIR. Based on 49,328 primary historical inspection reports obtained from the Paris MoU database in 2015-2017, those related to bulk carriers (i.e. 10000 records) are selected to build a BN risk model. The BN risk model provides a novel way to obtain the detention rates relating to different company performance levels and vessel quality. They can be used as important input in the subsequent game model construction. Through calculating every payoff during an inspection, a payoff matrix is utilized to present the new BN risk-based PSC game model.

The Nash equilibrium of the newly proposed game model will eventually reveal the optimal inspection policy for port authorities and motivate ship owners to improve their vessel quality and safety performance to mitigate maritime accidents. Supported by the empirical case study in Chapter 6, the managerial insights about the optimal inspection policy and the decision-making framework for port authorities can be obtained.

5.2 BASIC CONCEPTS IN GAME THEORY

5.2.1 Strategic games

A strategic game is a model of interactive decision-making in which each decision-maker chooses his plan of action once and for all, and these choices are made simultaneously. The model consists of a finite set of players, set of actions for each player, and a preference relation on the set of action profiles. Different from decision problem, which is the study of how to maximize expected utility in situations where there are no other participants making choices, strategic game is more complicated and practical. In a strategic game, each player may care not only about his own action but also about the actions taken by the other players, a feature that distinguishes the strategic games from decision problems. If the set of actions of every player is finite, then the game is finite.

The high level of abstraction of this game model allows it to be applied to a wide range of situations. A player may be an individual human being or any other decision-making entity like a government, a board of directors, an administration authority, and the leadership of a revolutionary movement, or even a flower or an animal. The model places no restrictions on the set of actions available to a player, which may, for example, contain just a few elements or be a huge set containing a complicated plan that covers a variety of contingencies. However, the range of application of the model is limited by the requirement that each player is associated with a preference relation. A player's preference relation may simply reflect the player's feelings about the possible outcomes or, in the case of an organism that does not act consciously, the chances of its reproductive success.

The fact that the model is so abstract is a merit to the extent that it allows applications in a wide range of situations, but is a drawback to the extent that the implications of the model cannot depend on any specific features of a situation. Indeed, very few conclusions can be reached about the outcome of a game at this level of abstraction; one needs to be much more specific to derive interesting results.

In some situations, the players' preferences are most naturally defined not over action profiles but over their consequences. When modelling the PSC inspection in this study, for example, port authorities and ship owners may set as the players, and the set of actions of each player are the choices like inspection or maintenance. Actually, it is the profit that matters, not the choices that generates the profit. To do so, a set of consequence (profit) is introduced, and a function from actions to consequence is generated. Hence, this kind of strategic game reflects a situation that the preference relation of each player is set over consequence.

Interpretation of the model

Normally, there are two kinds of interpretations.

One common interpretation is that strategic game is a model of an event that occurs only once. Each player knows the details of the game and the fact that all the players are rational, and the players choose their actions simultaneously and independently under this interpretation. Each player is unaware, when choosing his action, of the choices being made by the other players; there is no information (except the primitives of the model) on which a player can base his expectation of the other players' behaviour.

Another interpretation is that a player can form his expectation of the other players' behaviour based on information about the way that the game or a similar game was played in the past. Under this situation, an individual who plays the game many times must be concerned only with his instantaneous payoff and ignore the effects of his current action on the other players' future behaviour, which is slightly different from the former interpretation.

One thing to note that is for a situation to be modelled as a strategic game, it is important only that the players make decisions independently, no player being informed of the choice of any other player prior to making his own decision.

5.2.2 Payoff matrix

Under a wide range of circumstances, the preference relation of player in a strategic game can be represented by a payoff function (also called a utility function). The value of such a function is called payoff. If the payoff of one action A is higher than another action B, then action A has a higher priority and probability to be chosen as the strategy of this player.

In reality, payoffs are numbers that represent the motivations of the players. Depending on different games, payoffs may represent profit, quantity, continuous measures (cardinal payoffs), and/or the rank of desirable outcomes (ordinal payoffs).

In order to determine the optimal strategy for each player, a payoff matrix is usually applied to address the problem. It is an $m \times n$ matrix that gives the possible payoff of a two-person game when player 1 has m strategies and player 2 has n strategies. This visual representation approach can describe the payoff of each player under different strategy profiles in Table 5.1.

Table 5.1 An example of a payoff matrix

	C	*D*
A	w_1, w_2	y_1, y_2
B	x_1, x_2	z_1, z_2

(Source: Author)

Player 1's strategies are identified with the rows and player 2's with the columns. The two numbers in each cell are the players' payoffs when player 1 chooses the row strategy and player 2 chooses the column strategy. For example, the two numbers w_1 and w_2 in first cell means when player 1 chooses strategy *A* and player 2 chooses strategy *C*, the payoff of player 1 is w_1 and the payoff of player 2 is w_2.

Payoff matrix presents a visualized way to analyse the strategic game, and it is currently a widely used approach to figure out the optimal strategies of participating players.

5.2.3 Nash equilibrium

Nash equilibrium is the most commonly used solution concept in the game theory. It captures a steady state of the play of a strategic game in which each player holds the correct expectation about the other players' behaviour and acts rationally (Nash, 1950). Meanwhile, it does not attempt to examine the process by which a steady state is reached.

When it comes to a Nash equilibrium, no player has another action yielding an outcome that he prefers to that generated when he chooses a corresponding action, given that every other player chooses his or her Nash equilibrium action. Briefly, no player can profitably deviate, given the actions of the other players.

The following case named and interpreted by Tucker presents a simple example of Nash equilibrium (Tucker, 1983). Two criminals are caught in a crime and put into separate cells. The police will interrogate both of them, respectively. If they both confess, each will be sentenced to three years in jail. If only one of them confesses, he will be freed and used as a witness against the other, who will receive a sentence of four years. If neither confesses, they will both be convicted of a minor offence and spend one year in prison. The payoff matrix of this game is shown in Table 5.2.

Table 5.2 An example of obtaining Nash equilibrium

	Confess	*Not confess*
Confess	*3, 3*	*0, 4*
Not confess	*4, 0*	*1, 1*

(Source: Tucker, 1983)

If the two criminals decide to cooperate, the best strategy for them is that neither confesses and both of them only have to be sentenced to jail one year. However, in a strategic game, each player is rational and has an incentive to be a self-centred person, which means the players care more about their own benefits and therefore will not choose cooperation. In this case, no matter what one criminal choose, the other prefers '*confess*' to '*not confess*' as the former choice always generates a higher payoff than the latter one for every person. Hence, the Nash equilibrium of this example is '*Confess, Confess*'. This problem is called 'Prisoner's dilemma', which is one of the famous cases in game theory.

5.2.4 Mixed strategy Nash equilibrium

Mixed strategy Nash equilibrium is designed to model a steady state of a game in which the participants' choices are not deterministic but are regulated by probabilistic rules. For a strategic game, a member of action set of players is called a *pure strategy*. On the contrary, a member of the set of probability distribution of action set of players is called a *mixed strategy*. Based on this conception, a mixed strategy Nash equilibrium of a strategic game is a Nash equilibrium of its mixed extension.

There are a number of interpretations of mixed strategy Nash equilibrium, and some of them are shown as follows:

1) Mixed strategy Nash equilibrium entails a deliberate decision by a player to introduce randomness into his behaviour, representing the objectives of his choice.

2) Similar to Nash equilibrium, mixed strategy Nash equilibrium is explained as a stochastic steady state of an environment in which players act repeatedly and ignore any strategic link that may exist between plays.

3) A mixed strategy Nash equilibrium is a description of a steady state of the system that reflects elements missing from the original description of the game.

4) A mixed strategy Nash equilibrium is a profile of belief, each element in the equilibrium is a common belief of all the other players about this player's actions. Under this interpretation, each player chooses a single action rather than a mixed strategy. An equilibrium is a steady state of the players' beliefs, not their actions.

These interpretations explain the mixed strategy Nash equilibrium from many different aspects. Each of them has its limitation, leading to several criticisms of it. However, the discussions on the mixed strategy Nash equilibrium indicate its popularity and importance in the field of game theory.

5.3 THEORETICAL GAME MODEL BETWEEN PORT AUTHORITIES AND SHIP OWNERS

A game between a port authority and a ship owner is more like a 'supervise-being supervised' activity. In this game, the main object of the port authority is to optimize the social welfare (Florens & Foucher, 1999). Therefore, it takes measures to ensure maritime safety, such as the policies on maritime safety, the conventions on maritime security and the punishment of the illegal ship owners. Although these measures cannot completely eradicate potential maritime safety hazards, they can certainly stimulate ship owners to improve the quality of their vessels. Simultaneously, the ship owner aims at maximizing their benefits, resulting in the search for a balance between the cost and detention. The conflict of objectives forms the game relationship between the port authority and the ship owner.

The process of developing a game model consists of three essential steps: 1) confirming the participated players, 2) figuring out the strategy of each player, and 3) determining the payoff of each strategy. When making decisions, both port authorities and ship owners will make their choices based on the payoffs of the strategies under different situations. As one of the important factors in game model, the inspection risk plays a key role in determining the payoffs. Hence, in order to quantify the inspection risk, BN is combined with the game model for the first time to reflect the actual conditions in PSC after the implementation of NIR precisely. Meanwhile, the BN model proposed in this thesis takes into account company performance as an important risk factor influencing the inspection results, and the final model is able to reveal the detention rates under various conditions involving different company performance levels. In the subsequent game model construction, the detention rate can be used as an indicator of the company performance, presenting a game model between port authorities and ship owners considering the effect of company performance for the first time since PSC inspection regime changed.

As the objective of this section is to analyse the optimal inspection policy of port authorities after the implementation of NIR, 'Post-NIR' BN model is selected to help the work of game model construction. The process of building the game model is illustrated as follows.

5.3.1 Assumptions

Before constructing the game model, several assumptions are proposed to conform to the definition of the strategic game. Based on the definition and interpretations from Osborne & Rubinstein (1994), the following assumptions are made in this study:

1) The vessel type selected for constructing the game model is bulk carrier for two reasons: one is bulk carrier accounts for 20% of inspection records; second is the detention rate of bulk carrier is mostly the same as the average detention rate (for all vessel types), indicating that the bulk carrier can be used to represent the inspection system. (Explained in Chapter 4 in detail).

2) The two stakeholders in the PSC inspection game, the port authorities and the ship owners, are rational players. The purposes of the two stakeholders are presented as follows:

Ship owners: for maximizing personal interest

Port authorities: for minimizing social welfare losses

The conflicts between the objectives of two major stakeholders in the inspection game manifest that the PSC inspection game is a non-cooperative game[2].

3) The game is a strategic game, and each player holds the correct expectation about the other player's behaviour and acts rationally based on the information about the way that the game was played in the past.

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[2] A non-cooperative game is a game with competition between individual players and in which only self-enforcing (e.g. through credible threats) alliances (or competition between groups of players, called "coalitions") are possible due to the absence of external means to enforce cooperative behaviour (Osborn & Rubinstein, 1994; Friedman, 1991).

4) The players make decisions independently and simultaneously, and each player is unaware of the choices being made by the other players.

5) ‘Bulk carriers’ is classified into two types according to the maintenance effort of ship owners: standard vessels with effort *M* and sub-standard vessels with effort *m*. The reason for the classification is to conform to the PSC inspection system that marks the vessel passing the inspection as ‘standard vessel’ and the vessel failing to pass the inspection as ‘sub-standard’ vessel.

6) To simplify the calculation work, the accident losses caused by standard or sub-standard vessels are the same in this research[3].

5.3.2 Parameter identification

From the definition of the strategic game, it consists of three elements: 1) a finite set of players, 2) a nonempty set of strategies for each player and 3) a preference relation on the set of strategies, which can be represented by payoff.

Therefore, when building the inspection game in this study, the parameters need to be identified from these three aspects.

5.3.2.1 Players

It is obvious that the inspection game involves two players: port authorities and ship owners.

5.3.2.2 Strategies

Strategy of the port authorities

There are two strategies for the port authorities to treat the vessels arriving at their ports

- Inspect the vessel (with probability X)
- Not inspect the vessel (with the probability 1 – X)

[3] In fact, the accident losses of the two vessel types would be slightly different, because standard vessels may have more precautionary measures to deal with the maritime accidents than sub-standard vessels, thus leading to less loss when encountering unexpected cases.

Strategy of the ship owners

When confronted with the inspections, the ship owners can make either a high intensity effort to ensure the vessel standard or a low effort to leave the vessel sub-standard. The strategies are expressed as follow.

- High intensity effort: Standard vessels (with probability Y)
- Low effort: Sub-standard vessels (with probability 1-Y)

5.3.2.3 Payoffs

In section 5.2.2, 'payoffs' is defined as the numbers that represent the motivations of the players. It has a wide variety of forms, e.g. profit, rank, or quantity. According to the objectives of the players in PSC inspections, the 'payoffs' in the inspection games is defined as profit.

Based on the literature (Li, et al., 2015) and the inspection record reports, the payoff of the ship owner consists of the following components: expected detention cost, expected accident loss, inspection cost, maintenance cost and the port charges. Accordingly, the payoff of the port authority includes social welfare increase due to detention, the social welfare loss due to accidents, inspection cost, and the port charges.

These parameters influencing payoffs are explained with a particular reference to their state definitions as follows:

1) Expected detention cost

Related to the choice of the port authority, the expected detention cost is the risk that the ship owner faces when accepting inspections. Only when the port authority decides to inspect the vessel, is it incurred. Meanwhile, because the inspection results can be subject to errors, there exists detention rate (likelihood) for both standard vessels and sub-standard vessels. Hence, the expected detention cost is the product of detention rate and detention-related cost. (i.e. *expected detention cost = detention rate (D) * detention related cost* (C_{D1}))

Detention rate: D

Detention rate is the probability that a vessel fails to pass the inspection. Meanwhile, it acts like a bond linking the ship owner, port authority and ISM Company. Its value can be obtained through the BN model in Chapter 3.

Detention-related cost of the ship owner: C_{D1}

In general, a ship is not released from detention before all necessary repairs are made, and it even needs to sail to another shipyard for repair if it is not possible to repair these deficiencies at the place of inspection. Such detention-related cost during the detention period is summarized as the consequence of detention.

According to the definition of risk (i.e. *Risk = Likelihood * Consequence*), the expected detention cost is the product of detention rate and detention-related cost.

*Expected detention cost = detention rate (D) * detention related cost* (C_{D1})

2) Expected social welfare increase due to detention

Other than the expected detention cost to the ship owner, detention also brings social welfare increase to the port authority. The punishment to ship owners makes the vessel safer and better, as well as generating additional earnings for the port. This part is set as C_{D2}.

However, the detention-related cost to the ship owner does not equal to the increase in social welfare because some cost types of the former are not included in the latter, e.g. operating cost, fuel cost (if a ship needs to sail to another place for repair).

Similar to expected detention cost, the expected social welfare increase is the product of detention rate and the punishment.

*Expected social welfare increase = detention rate (D) * punishment* (C_{D2})

3) Expected accident loss

Expected accident loss is the risk of the vessel being caught in maritime accidents. It is composed of accident rate and accident loss.

Accident rate: P

Maritime transportation is risky and hazardous. When sailing at sea, every vessel will face the dangers of maritime accidents. On this occasion, ship owners' effort really matters. A standard and compliant vessel is less likely than a sub-standard one to be caught in an accident.

- P_M: accident probability of standard vessel
- P_m: accident probability of sub-standard vessel

Accident loss: C_A

Accident loss is the consequential cost related to the ship owner when an accident happens, e.g. vessel value, cargo value, casualties. Different effort of the ship owner can influence the severity of loss, and standard vessel is more likely to better deal with emergencies and cause less loss. Because of limited data availability, only the value of the vessel is chosen to represent the accident loss in this thesis.

- C_{A1}: accident loss of standard vessel
- C_{A2}: accident loss of sub-standard vessel

As a result, the expected accident loss is calculated via the following equation,

$$Expected\ Accident\ loss = accident\ rate\ (P) * accident\ loss\ (C_A)$$

4) Social welfare loss of accidents: C_{SW}

When an accident happens, it will lead to the loss of social welfare. This type of loss includes environmental pollution damage, salvage cost, recovery cost and so on. Port authorities should consider these losses when calculating social welfare loss. Similar to accident loss to the ship owner, different vessel safety levels will cost differently.

- C_{SW1}: social welfare loss of standard vessel
- C_{SW2}: social welfare loss of sub-standard vessel

5) Inspection cost C_I

When making the decision to inspect a vessel, the port authority needs to spend money and human resources on it. At the same time, it will incur a cost to the ship owner as well.

- C_{I1}*:* inspection cost of port authority
- C_{I2}*:* inspection cost of ship owner

6) Maintenance cost of the ship owner: $C\ (P_i,\ i)$

In order to pass the inspection and avoid maritime accidents, the ship owner will spend a certain amount of money and resources, including technological, operational and preventive costs. The more they invest the higher probability to pass the inspection and avoid the occurrence of accidents. This type of cost is presented as $C\ (P_i,\ i),\ i = m,\ or\ M$

- $C\ (P_M,\ M)$: cost to maintain a standard vessel
- $C\ (P_m,\ m)$: cost to maintain a sub-standard vessel

7) Port charges: C_{PC}

When the vessel arrives at the port, it will face some different types of charges from the port, e.g. tonnage dues, harbour dues, pilotage dues, berth hire charges and anchorage fee. Unlike detention cost and inspection cost, costs in this aspect are unavoidable for all vessels, no matter whether the vessel is standard or sub-standard, detained or not detained.

5.3.3 The payoff matrix

When formulating the payoff matrix, the primary work is to figure out the payoffs under different strategy combinations. Based on the identified parameters and the information provided above, the payoff functions of port authorities and ship owners under different situations are provided in Equation (5-1) and Equation (5-2). For port authorities, their payoffs are associated with social welfare increment of vessel detention, social welfare loss of maritime accidents, costs paid for PSC inspections and port charges from arriving vessels; for ship owners, the possible detention cost, the possible maritime accident loss, the inspection costs, and the charges at port are the units constituting the payoffs. For the different pairs of strategy combinations, the payoff of each stakeholder can be obtained via inserting the values of parameters reflecting the investigated situation into corresponding functions.

The equation to calculate the payoffs of the port authority and the ship owner under different situations are presented in Equation (5-1) and Equation (5-2) as follows:

Payoff of the port authority = (Expected social welfare increase due to detention – Expected social welfare loss of accident - inspection cost + port charges) (5-1)

Payoff of the ship owner = - (expected detention cost + expected accident loss + inspection cost + maintenance cost + port charges) (5-2)

5.3.3.1 Scenario 1: Inspection (port authority) and standard vessel (ship owner)

1) Payoff of the port authority

There are two possible results: detention or no detention. From Equation (5-1), there are four components to form the payoff.

Expected social welfare increase exists only when detention occurs, hence it is C_{D2} when the vessel is detained, and otherwise it is 0.

Expected social welfare loss of an accident always exists whatever the inspection result is.

In this scenario, the accident rate is P_M; and the social welfare loss when an accident happens is C_{SW1}. Therefore, the expected social welfare loss is $P_M \times C_{SW1}$. Other components, the inspection cost and port charges, can be easily obtained as C_{I1} and C_{PC}, respectively.

In summary, the payoff of the port authority is:

- If the vessel is detained (D_M)
  $C_{D2} - P_M \times C_{SW1} - C_{I1} + C_{PC}$
- If the vessel is not detained (1- D_M)
  $0 - P_M \times C_{SW1} - C_{I1} + C_{PC}$

Overall payoff:

$$\begin{aligned} & D_M \times (C_{D2} - P_M \times C_{SW1} - C_{I1} + C_{PC}) + (1 - D_M) \times (0 - P_M \times C_{SW1} - C_{I1} + C_{PC}) \\ & = D_M \times C_{D2} - P_M \times C_{SW1} - C_{I1} + C_{PC} \end{aligned}$$

2) Payoff of the ship owner

According to Equation (5-2), the payoff of the ship owner consists of five parts.

Similar to expected social welfare increase, the expected detention cost is also influenced by the inspection results. If the vessel is detained, the detention-related cost is C_{D1}. If not, the ship owner does not need to pay anything.

Since the vessel is at standard safety level, the probability it encounters an accident is P_M, while the consequence of the maritime accident for the ship owner is C_{A1}. Hence, the expected accident loss is $P_M \times C_{A1}$.

In addition, to ensure the vessel's compliance with regulation standards, it will cost the ship owner $C\ (P_M,\ M)$ to maintain the vessel. Furthermore, the inspection cost C_{I1} and the port charges C_{PC} are important expenditure for the ship owner. In summary, the payoff of the ship owner is:

- If the vessel is detained (D_M)
  $-(C_{D1} + P_M \times C_{A1} + C_{I2} + C(P_M, M) + C_{PC})$
- If the vessel is not detained (1- D_M)
  $-(0 + P_M \times C_{A1} + C_{I2} + C(P_M, M) + C_{PC})$

Overall payoff:

$$D_M \times [-(C_{D1} + P_M \times C_{A1} + C_{I2} + C(P_M, M) + C_{PC})] + (1 - D_M) \times [-(0 + P_M \times C_{A1} + C_{I2} + C(P_M, M) + C_{PC})]$$
$$= -(D_M \times C_{D1} + P_M \times C_{A1} + C_{I2} + C(P_M, M) + C_{PC})$$

5.3.3.2 Scenario 2: Inspection (port authority) and sub-standard vessel (ship owner)

In this scenario, the way to calculate the payoffs for each player is similar to scenario 1. The components of payoff need to change to the corresponding values of sub-standard vessels based on the information provided in parameter identification section, e.g. D_M to D_m, P_M to P_m, $C\ (P_M, M)$ to $C\ (P_m, m)$, C_{A1} to C_{A2} and C_{SW1} to C_{SW2}.

However, when a sub-standard vessel is detained, it is asked to repair these deficiencies until the vessel complies with the regulations of the port. This process will improve the safety level of the vessel and reduce the accident probability. In this study, in order to simplify the model, the accident rate is set as P_M for the sub-standard vessel after its detention. At the same time, the expected accident loss and expected social welfare loss also change as follows.

$$\text{Expected accident loss} = \begin{cases} P_M \times C_{A1}, & \text{detention} \\ P_m \times C_{A2}, & \text{no detention} \end{cases}$$

$$\text{Expected social welfare loss} = \begin{cases} P_M \times C_{SW1}, & \text{detention} \\ P_m \times C_{SW2}, & \text{no detention} \end{cases}$$

1) Payoff of the port authority

- If the vessel is detained (D_m)

  $C_{D2} - P_M \times C_{SW1} - C_{I1} + C_{PC}$
- If the vessel is not detained (1- D_m)

  $0 - P_m \times C_{SW2} - C_{I1} + C_{PC}$

Overall payoff:

$$D_m \times (C_{D2} - P_M \times C_{SW1} - C_{I1} + C_{PC}) + (1 - D_m) \times (0 - P_m \times C_{SW2} - C_{I1} + C_{PC})$$

$$= D_m \times C_{D2} - P_m \times C_{SW2} - C_{I1} + C_{PC} - D_m \times (P_M \times C_{SW1} - P_m \times C_{SW2})$$

2) Payoff of ship owner

- If the vessel is detained (D_m)

  $-(C_{D1} + P_M \times C_{A1} + C_{I2} + C(P_m, m) + C_{PC})$

- If the vessel is not detained (1- D_m)

  $-(0 + P_m \times C_{A2} + C_{I2} + C(P_m, m) + C_{PC})$

Overall payoff:

$$D_m \times [-(C_{D1} + P_M \times C_{A1} + C_{I2} + C(P_m, m) + C_{PC})] + (1 - D_m) \times [-(0 + P_m \times C_{A2} + C_{I2} + C(P_m, m) + C_{PC})]$$

$$= -(D_m \times C_{D1} + C_{I2} + P_m \times C_{A2} + C(P_m, m) + C_{PC} + D_m \times (P_M \times C_{A1} - P_m \times C_{A2}))$$

If the port authority does not inspect the vessel, the detention will not occur and the values of the inspection-related parameters will be *0*, including the expected detention cost, the expected social welfare loss and the inspection cost. Meanwhile, the risk of being detained is free. As a result, the payoff equation is simplified as:

Payoff of the port authority = (– Expected social welfare loss of accident + port charges) (5-3)

Payoff of the ship owner = - (Expected accident loss + maintenance cost + port charges) (5-4)

5.3.3.3 Scenario 3: No inspection (port authority) and standard vessel (ship owner)

In this scenario, the payoffs of the port authority and ship owners are obtained according to the Equation (5-3) and Equation (5-4), respectively. Because the port authorities choose not to inspect the vessel, the calculation of payoff does not need to be divided into two parts. The following expressions present the payoffs of each stakeholder.

1) Payoff of port authority

$$-P_M \times C_{SW1} + C_{PC}$$

2) Payoff of ship owner

$$-(P_M \times C_{A1} + C(P_M, M) + C_{PC})$$

5.3.3.4 Scenario 4: No inspection (port authority) and sub-standard vessel (ship owner)

Similar to scenario 3, the payoffs of the port authority and ship owners are obtained according to the Equation (5-3) and Equation (5-4), respectively. The following expressions present the payoffs of each stakeholder under this case.

1) Payoff of port authority

$$-P_m \times C_{SW2} + C_{PC}$$

2) Payoff of ship owner

$$-(P_m \times C_{A2} + C(P_m, m) + C_{PC})$$

5.3.3.5 The payoff matrix of PSC inspection game under NIR

In the above scenario simulation, each scenario represents a strategy profile in the PSC inspection game. The final payoff matrix of the PSC inspection game under NIR can be obtained through summarizing the payoffs in every situation.

Table 5.3 depicts the payoff matrix. The actions identified with rows are the strategies of port authorities, while the actions in column are the ship owners' choices. The two expressions in the boxes represent the payoff of stakeholders when port authorities choose row action and ship owners choose column action. The above expressions in the boxes are the payoffs of port authorities under this scenario, while the nether expressions describe the payoffs of ship owners correspondingly.

Table 5.3 Payoff matrix of PSC inspection game

	Standard vessel	***Sub-standard vessel***
Inspection	$D_M \times C_{D2} - P_M \times C_{SW1} - C_{I1} + C_{PC}$ $-(D_M \times C_{D1} + P_M \times C_{A1} + C_{I2} + C(P_M, M) + C_{PC})$	$D_M \times C_{D2} - P_m \times C_{SW2} - C_{I1} + C_{PC} - D_m \times (P_M \times C_{SW1} - P_m \times C_{SW2})$ $-(D_m \times C_{D1} + C_{I2} + P_m \times C_{A2} + C_{PC} + C(P_m, m) + D_m \times (P_M \times C_{A1} - P_m \times C_{A2}))$
No inspection	$-P_M \times C_{SW1} + C_{PC}$ $-(P_M \times C_{A1} + C(P_M, M) + C_{PC})$	$-P_m \times C_{SW2} + C_{PC}$ $-(P_m \times C_{A2} + C(P_m, m) + C_{PC})$

(Source: Author)

5.3.4 Nash equilibrium solution

For the inspection game in this study, the choices of players are not deterministic but are regulated by probabilistic rules. The Nash equilibrium under this condition is called mix strategy Nash equilibrium, and the aim of this section is to find out the mix strategy Nash equilibrium for the PSC inspection game.

5.3.4.1 The existence of Nash equilibrium

To find out the mixed strategy Nash equilibrium for the proposed game model, the first thing is to ensure that there exists an equilibrium point forming the steady state of the game model. If the interests of port authorities and ship owners were diametrically opposed, then the inspection game would have no Nash equilibrium point.

According to a theorem presented by Osborne and Rubinstein (1994) in their book named 'A course in Game theory',

Theorem 1: Every finite strategic game has a mixed strategy Nash equilibrium.

(The proof for the theorem is not illustrated here, as it requires complicated mathematical knowledge.)

In the PSC inspection game, there are two players (the port authority and the ship owner), and each player has two actions and their preference. The settings of our game conform to the definition of finite strategic game. Hence, according to *theorem 1*, the PSC inspection game proposed in this research has a mixed strategy Nash equilibrium.

5.3.4.2 Mixed strategy Nash equilibrium - Osborne & Rubinstein approach

There are various ways to obtain the Nash equilibrium solutions to the game models. In this research, an approach proposed by Osborne and Rubinstein (1994) is applied, which is a proper and convenient way to deal with the cases like PSC inspection game.

According to Osborne and Rubinstein (1994), there is an important property of mixed strategy Nash equilibrium that is useful when calculating the equilibria.

Theorem 2: For a finite strategic game G, α^* ***is a mixed strategy Nash equilibrium of G if and only if for every player i in the game, every pure strategy in the support of*** α_i^* ***is the***

best response to $\boldsymbol{\alpha^*_{-i}}$.

($\boldsymbol{\alpha_i}$ means the mixed strategy of player *i* in the mixed Nash equilibrium, while $\boldsymbol{\alpha_{-i}}$ means the mixed strategies of players without player *i*.)

Proof: (Proof by contradiction)

First, let us suppose that there exists an action of player *i* called a_i in the support of the mixed strategy Nash equilibrium α^* that is not a best response to α^*_{-i}. Then player i can increase his payoff by replacing this action to another action that is a best response to α^*_{-i}. Hence, this new mixed strategy combination is superior to α^*, making α^* not the equilibria of the game model, which is contradictory to the settings.

Second, suppose that there exists another mixed strategy α_i' that gives player i a higher payoff than α_i^* in response to α^*_{-i}. Hence, there must be at least one action in the support of α_i' output a higher payoff than some actions in the support of α_i^*. Under this occasion, not all the actions in the support of α_{i}^* are the best response to $\alpha^*_{-\mathrm{i}}$, which is also contradictory to the settings in the theorem.

Q.E.D.

To simplify the description of *Theorem 2* and transform it into words that are easy to understand, the following simplified theorem is presented.

Theorem 3: Every action in the support of any player's equilibrium mixed strategy yields that player the same payoff.

One thing worth noting is that the requirement that the players' preferences can be represented by expected payoff functions plays a key role in these characterizations of mixed strategy equilibrium, which is also suitable and feasible for the PSC inspection game. Hence, this approach is suitable and preferable for the Nash equilibrium calculation in our research. However, the results do not necessarily hold for other theories of decision-making under uncertainty.

The following example further clarifies this approach and illustrates how the mixed strategy Nash equilibrium can be found according to *Theorem 3*.

Table 5.4 An example of how to calculate Nash equilibrium

	Bach – $a_2(B)$	*Stravinsky – $a_2(S)$*
Bach – $a_1(B)$	*2, 1*	*0, 0*
Stravinsky – $a_1(S)$	*0, 0*	*1, 2*

(Source: A course in Game theory, 1994)

Consider two people are planning to go to a concert, they have two choices: Bach or Stravinsky. The payoffs of each player are presented in Table 5.4, where these values represent their preferences. A large number means the player prefers it much. Now we show how to calculate the mixed strategy Nash equilibrium in this example based on *Theorem 3*.

Suppose (a_1, a_2) is the mixed strategy Nash equilibrium for this example, where a_1 is the choice of player 1, a_2 represents player 2' action. According to Theorem 3, given a_2, player 1's action Bach and Stravinsky yield much the same payoff for him, so that we have

$$\begin{cases} 2\,a2(B) + 0\,a2(S) = 0\,a2(B) + 1\,a2(S) \\ a2(B) + a2(S) = 1 \end{cases}$$

Thus, we have $a2(B) = \frac{1}{3}, a2(S) = \frac{2}{3}$

Similarly, given a_1, player 2's two actions yield much the same payoff for his too, the result shows $a1(B) = \frac{2}{3}, a1(S) = \frac{1}{3}$. Therefore, the only non-degenerate mixed strategy Nash equilibrium of the game is $(\left(\frac{2}{3}, \frac{1}{3}\right), \left(\frac{1}{3}, \frac{2}{3}\right))$.

Based on *Theorem 3* and the provided example, the mixed strategy Nash equilibrium solution for PSC inspection game can be obtained.

Table 5.5 The simplified payoff matrix

	Standard vessel(Y)	*Sub-standard vessel(1-Y)*
Inspection(X)	*PA_{11}, SO_{11}*	*PA_{12}, SO_{12}*
No inspection(1-X)	*PA_{21}, SO_{21}*	*PA_{22}, SO_{22}*

(Source: Author)

Table 5.5 presents the simplified payoff matrix for the convenience of calculation. The first number in each cell represents the payoff of the port authority, while the second represents that of the ship owner.

In terms of the payoffs in this table, the equation set according to *Theorem 3* is shown as follows

$$\begin{cases} Y \times PA_{11} + (1-Y) \times PA_{12} = Y \times PA_{21} + (1-Y) \times PA_{22} \\ X \times SO_{11} + (1-X) \times SO_{21} = X \times SO_{12} + (1-X) \times SO_{22} \end{cases}$$

Where PA means the port authority, SO means the ship owner. The first equation means 'Inspection' and 'No inspection' of the port authority generate the same payoff for PA given the ship owner's optimal choice, while the second equation indicates the 'Standard maintenance effort' and 'Sub-standard maintenance effort' yield the same payoff for SO given the PA's optimal choice.

The solution to this equation set presents the probability of each action in support of mixed strategy Nash equilibrium.

$$\begin{cases} X = \dfrac{SO_{22} - SO_{21}}{SO_{11} + SO_{22} - SO_{12} - SO_{21}} \\ Y = \dfrac{PA_{22} - PA_{12}}{PA_{11} + PA_{22} - PA_{12} - PA_{21}} \end{cases} \tag{5-5}$$

In addition, the final mixed strategy Nash equilibrium is *((X, 1-X), (Y, 1-Y))*.

After plugging the payoffs into the corresponding places in Equation (5-5), the mixed strategy Nash equilibrium of the strategic game between the port authority and the ship owner is presented. Additionally, considering the fact that the players in the game may not always act as the mixed strategy Nash equilibrium tells them, the final Nash solution to the PSC inspection game is presented in Equation (5-6) and Equation (5-7), respectively:

$$X^* = \begin{cases} 0, & Y^* > Y_0 \\ X_0, & Y^* = Y_0 \\ 1, & Y^* < Y_0 \end{cases} \tag{5-6}$$

$$Y^* = \begin{cases} 1, & X^* > X_0 \\ Y_0, & X^* = X_0 \\ 0, & X^* < X_0 \end{cases} \tag{5-7}$$

where $X_0 = \frac{P_M \times C_{A1} - P_m \times C_{A2} + C(P_M, M) - C(P_m, m)}{C_{D1} \times (D_M - D_m) + D_m \times (P_M \times C_{A1} - P_m \times C_{A2})}$, $Y_0 = \frac{D_m \times (P_M \times C_{SW1} - P_m \times C_{SW2}) - D_m \times C_{D2} + C_{I1}}{C_{D2} \times (D_M - D_m) + D_m \times (P_M \times C_{SW1} - P_m \times C_{SW2})}$

This means that if $Y^* > Y_0$, the port authority will not inspect the vessel; if $Y^* < Y_0$, the port authority will inspect the vessel. Only when $Y^* = Y_0$ will the port authority choose the mixed strategy $X^* = X_0$. The same goes to the ship owner.

According to assumption (6) in Section 5.3.1, the accident loss under standard and sub-standard conditions are set the same ($C_{A1} = C_{A2} = C_A^0$, where C_A^0 is a constant no matter whether the vessel is standard or not). Therefore, the final solution is defined as follows.

$$X^* = \begin{cases} 0, & Y^* > Y_0 \\ X_0, & Y^* = Y_0 \\ 1, & Y^* < Y_0 \end{cases} \tag{5-8}$$

$$Y^* = \begin{cases} 1, & X^* > X_0 \\ Y_0, & X^* = X_0 \\ 0, & X^* < X_0 \end{cases} \tag{5-9}$$

where $X_0 = \frac{(P_M - P_m)\times C_A{}^0 + C(P_M,M) - C(P_m,m)}{C_{D1}\times(D_M - D_m) + D_m\times C_A{}^0\times(P_M - P_m)}$, $Y_0 = \frac{D_m\times(P_M\times C_{SW1} - P_m\times C_{SW2}) - D_m\times C_{D2} + C_{I1}}{C_{D2}\times(D_M - D_m) + D_m\times(P_M\times C_{SW1} - P_m\times C_{SW2})}$

5.3.5 Further improvement of the game model

The theoretical game model between the PA and SO in PSC inspection is presented. However, it is not perfect. Some settings of the game model are simplified and idealized because of the scarcity of related information and research. In this part, the further improvements to the game model are presented, guiding the direction of future research on this topic.

1) As stated in the assumption part, the players make decisions independently and simultaneously, and each player is unaware of the choices being made by the other players. However, in real cases, the port authorities have advantages over ship owners in PSC inspections, i.e. they formulate the PSC inspection policies, and they have the right to punish the ship owners for illegal actions. The advantages port authorities have against ship owners may enable them to make decisions first, in spite of the truth that the ship owners will observe their actions. On this occasion, the Nash solution is not suitable for the stakeholders in the game anymore. Instead, the Stackelberg equilibrium solution is preferred to tackle the scenarios like that.

Further research should consider this case to improve the game model, making it a more realistic mathematical model.

2) When a sub-standard vessel is detained, it is asked to repair these deficiencies until the vessel complies with the regulations of the port. This process will improve the safety level of

the vessel and reduce the accident probability. In this study, the accident rate of the sub-standard vessel after the repair is set as the same as the standard vessel in order to simplify the model.

In fact, the relationship between the vessel quality and the accident probability might be expressed by a particular function. If only classifying the accident probability into two types (standard and sub-standard), the setting would be too general to affect the final solutions to the model. Future work should pay more attention to the investigation into the relationship between the two aspects.

3) The accident loss under standard and sub-standard conditions are set the same when constructing the game model. The assumption is mainly for the later empirical case study part. The mixed strategy Nash solution is complicated and consists of many parts, if the accident loss was classified into several conditions, the calculation work would be enormous and could hardly be done manually. Nevertheless, the accuracy of the game model is influenced because of the assumption.

As many maritime consultancies have conducted related research and published the reports containing the information of the relationship between vessel quality and accident loss, for example, the Drewry Shipping Consultants Ltd, the game model would be improved a lot if the related statistics were collected and considered in the game model.

CHAPTER 6 AN EMPIRICAL STUDY TO DEMONSTRATE THE SIGNIFICANCE OF THEORETICAL GAME MODEL

In this chapter, a case study based on the inspection records from 2015-2017 is applied to facilitate the theoretical optimal inspection rate obtained from the game model in Chapter 5. The results reveal several trends of the optimal inspection rates, which enable port authorities to rationalize their inspection policies and ship owners to improve their vessel performance, and consequently maritime safety as a whole. Meanwhile, several suggestions are proposed to help port authorities manage the PSC inspection process more effectively.

6.1 INTRODUCTION

To characterize the optimal inspection policy for bulk carriers with respect to the Paris MoU, Nash equilibrium solutions need to be analysed through a numerical case. Through transforming the symbols in the theoretical Nash solutions into real values, the optimal inspection rates under real cases or situations are obtained. The analysis on the resulting values will provide important insights for port authorities when making inspection regulations.

Because the theoretical optimal inspection rates are obtained via the game model constructed after the implementation of NIR, the empirical study conducted in this chapter is based on the inspection records from 2015-2017.

However, it is very difficult, if not impossible, to acquire the data information of all parameters. Previous scholars chose to simulate the parameter values or discuss them by empirical data (Florens & Foucher, 1999). Nevertheless, there exists too much noisy vessel data, which requires a screening process before using them in the thesis.

In this chapter, data comes from three different databases, as shown in Table 6.1.

Table 6.1 Database and sources

Database	**Sources**
Basic vessel information database	World Shipping Encyclopedia
Casualty database	IMO, Lloyd's Register of Shipping
PSC inspection database	Paris MoU online inspection database

The objective focuses on finding out the optimal inspection policy for the port authority based on the proposed Nash solutions in Chapter 5.

The basic vessel information database is mainly compiled from the World Shipping Encyclopedia (WSE). It describes each vessel, with over 200 variables such as identity (IMO) number, nationality, date of building, tonnage, etc. However, most of the variables are not related to the research and not useful for the empirical study. In fact, only several major variables representing the important aspects of the vessels are selected to help us conduct the case study. The approximate capacity of the database is 130,000 vessels, and 7% of them is lost vessels.

The casualty dataset contains over 10,000 maritime accident records derived from IMO database and Lloyd's Register from 1979 until now. The casualty dataset includes accident records of collisions, contacts, fires and explosions, foundering, hull/machinery damage, and miscellaneous wrecks/stranding/groundings. However, in this research, accident types are not within our consideration. The casualty dataset is constructed and applied to figure out where the accident happened. The combination of casualty dataset and basic information dataset plays an important role in calculating the important parameters in the game model.

The PSC inspection dataset is the same as applied to construct the BN models of PSC inspection in Chapter 3. It consists of two parts: one is the inspection records from 2005 to 2008; the other is the inspection records from 2015 to 2017. All the inspection records collected are the inspections of bulk carriers that happened within the operation of the Paris MoU. It is used to calculate the detention rate of different vessel types when substituting into the proposed BNs.

Additionally, the BN model utilized to conduct the empirical study is the 'Post-NIR' model, because the game model developed in Chapter 5 focuses on the game relationship between the port authority and the ship owner after the implementation of NIR. Therefore, the 'Post-NIR' BN is the correct and proper model for the empirical study aiming at demonstrating the significance of the theoretical game model.

6.2 DETERMINATION OF THE PARAMETER VALUES

6.2.1 Detention rate through BN

In Chapter 3, the 'Post-NIR' BN model is proved reliable and able to predict the detention rate of PSC inspection when any new evidence is observed and collected. Hence, based on the function, the detention rates of different safety levels of any investigated vessel can be obtained.

6.2.1.1 Standard vessels

If the ship owner makes a high intensity effort in maintaining the vessel, the vessel will be maintained at a standard safety level and reach the criteria of inspection regulations. During an inspection, the detention risk of the vessel is relatively low, which means the two comprehensive factors 'inspection group' and 'vessel group' that represents two aspects of detention risk are both at the low level.

Hence, the scenario in which both 'vessel group' and 'inspection group' are at 'low detention risk' state in BN represents the standard bulk carriers, From the BN reasoning, the detention rate is calculated as 0.46% (decrease from the average 3.25%).

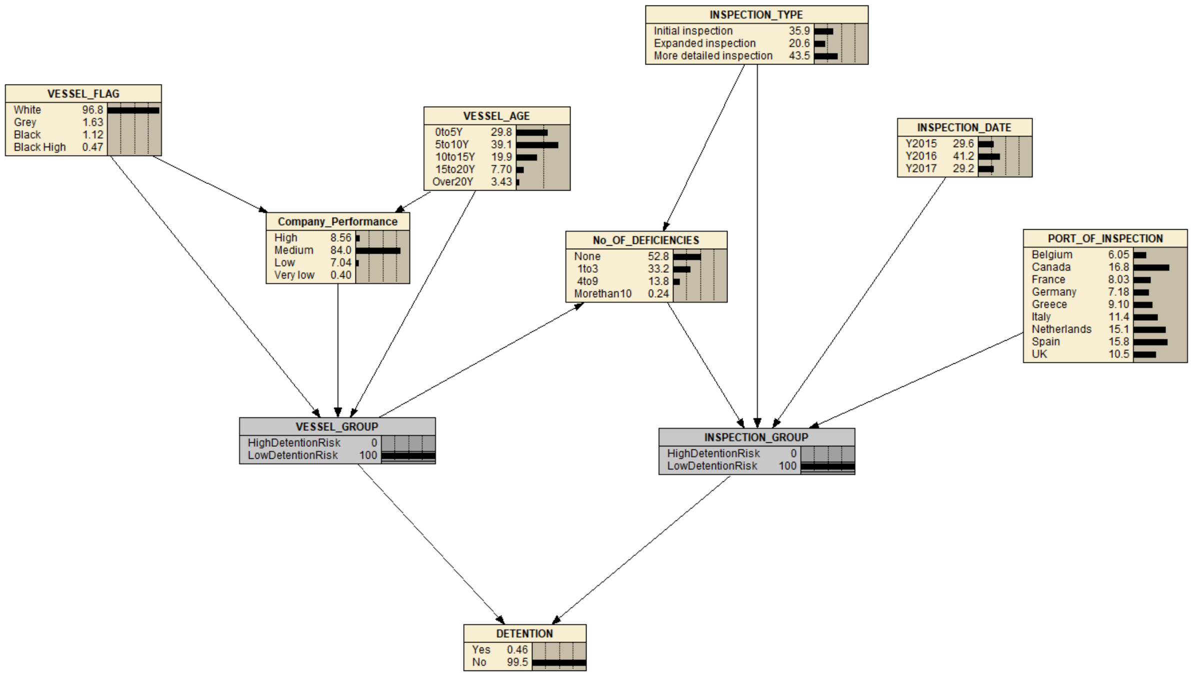

Figure 6.1 The detention rate of standard vessels

(Source: Author)

6.2.1.2 Sub-standard vessels

Accordingly, a sub-standard vessel is more likely to be caught in detention, indicating the two major risk factors that reflect the detention risk, 'vessel group' and 'inspection group', are at the 'high detention risk' state. The result of the BN reasoning reveals that the detention rate of a sub-standard vessel is 58.8% (increased from the average 3.25%).

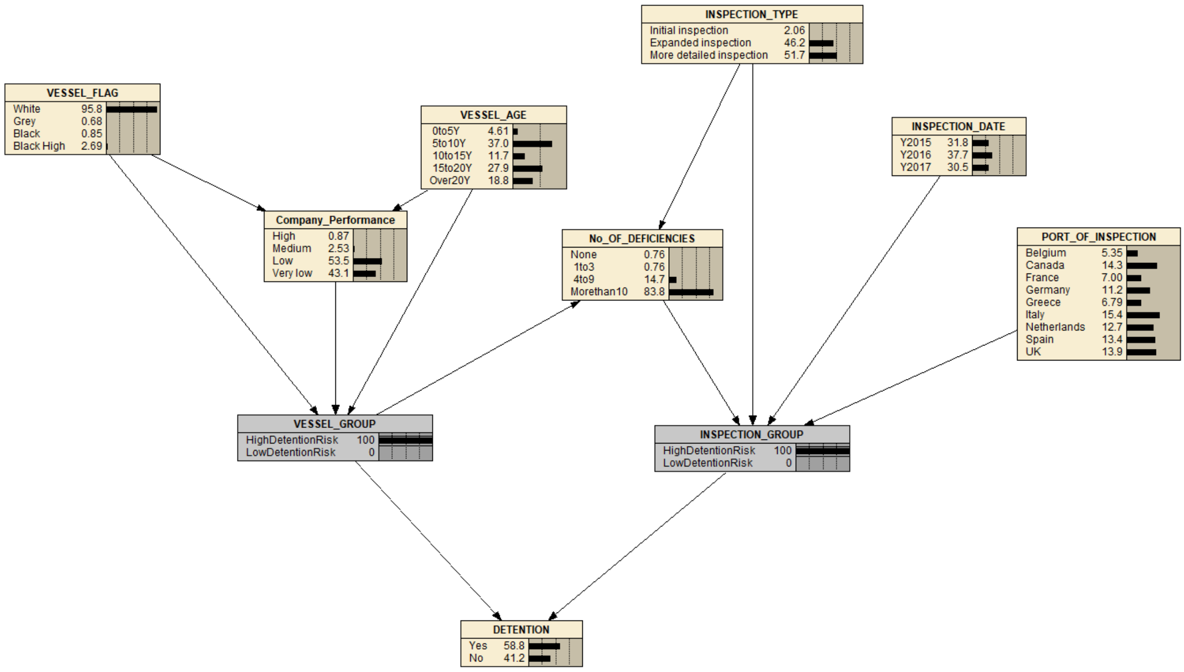

Figure 6.2 Detention rate of sub-standard vessels

(Source: Author)

6.2.2 Maintenance cost and accident loss

The maintenance cost is crucial to the ship owner and it is affected by a large number of factors, e.g. vessel age, material price, regional differences and damage degree. In addition, the effort of the ship owner also needs to be considered as an important factor.

Table 6.2 shows the maintenance cost under different conditions. It contains the maintenance cost of bulk carriers with different sizes and ages in a certain period. For example, the repair and maintenances cost for a young bulk ship with standard effort is US $200,175, while it is only US $120,105 with sub-standard effort (Drewy Shipping Concultants, 2012).

According to UNCTAD Review of Maritime Transport 2016, there are five types of bulk carriers: small, handysize, handymax, panamax and capesize. The size of the five types of vessels is incremental. Based on this, vessel size in this thesis is separated into two states: small, handysize and handymax bulk carriers as 'Small'; panama and capesize bulk carriers as 'Large'.

Vessel age is classified into three groups 'Young 0-5 years', 'Medium 6-10 years' and 'Old over 10 years'.

Table 6.2 Estimated approximate repair and maintenances under different conditions (US$)

Vessel size	Small					
Vessel age	Young		Medium		Old	
SO's effort	Stan	Sub	Stan	Sub	Stan	Sub
Bulk carrier	200175	120105	440385	190166	447057	266900
Vessel size	Large					
Vessel age	Young		Medium		Old	
SO's effort	Stan	Sub	Stan	Sub	Stan	Sub
Bulk carrier	319650	191790	703230	303667	713885	426200

Source: Drewy Shipping Consultants Ltd.

Meanwhile, as mentioned in parameter identification, the value of vessels is viewed as the accident loss to ship owners due to the data acquisition issue. Therefore, the price of second-hand vessels is used as the accident loss in this project, as it is a good indicator of the market value of the vessels.

Table 6.3 Estimated accident loss under different conditions (US$M)

Vessel size	Small			Large		
Vessel age	Young	Medium	Old	Young	Medium	Old
Bulk carrier	-31	-28	-11	-67	-53	-20

Source: Drewy Shipping Consultants Ltd

6.2.3 Accident rate

The accident rate is calculated by using a logistic regression approach (Wang, et al., 2017), which is an exponential function of various influencing factors. Normally, there are two types of logistic regression: binary logistic regression and multinomial regression.

In a multinomial regression, the dependent variable y is multinomial, and is modelled with different range of values for different status. Usually, the discrete-dependent variable is specified in the form of unobserved but continuous variable y^*, where $y^* \in (-\infty, +\infty)$.

Consider an independent variable set $\boldsymbol{X} = (x_1, x_2, \cdots, x_n)$ leading to the dependent variable y, where each independent variable has several status (j). Defining the unobserved variable y^*

as a function of $\boldsymbol{X}$,

$$y = \sum_{i=1}^{n} \sum_{j=1}^{m-1} \beta_{ij} x_{ij} + \varepsilon \tag{6-1}$$

Where β_{ij} represents the contribution of x_i in status j, ε is an unobserved stochastic component, and the value of x_{ij} is defined as $x_{ij} = 1$ when status j of x_i occurs, otherwise $x_{ij} = 0$.

Therefore, we can get the conditional probability of y under a configuration of independent variable set $\boldsymbol{X^0}$ through multinomial regression:

$$P(\mathrm{y} = y_i) = \frac{e^{\beta_i \boldsymbol{X^0} + \varepsilon}}{1 + \sum_{i=1}^{m-1} e^{\beta_i \boldsymbol{X^0} + \varepsilon}} \tag{6-1}$$

Where y_i represents the j-th status of y, and m the number of status of y.

Specific to the maritime accidents, Equation (6-1) can be transformed into the following Equation (6-3)

$$y = \beta_0 + \beta_1 VA + \beta_2 VS + \sum_{i=1}^{5} \beta_{i+2} VT_i + \beta_8 CS + +\beta_9 FS + \sum_{j=1}^{30} \beta_{j+9} Z_j + \varepsilon \tag{6-3}$$

where:

y: The probability of the maritime accidents, *y=1* if the accident happens, *y=0* if the accident not happens.

VA: vessel age.

VS: vessel size.

VT: vessel type. *VTi=1* if it is a dry cargo ship, otherwise *VTi=0, i = 1, 2, ..., 4* indicating the five different vessel types, namely dry cargo, bulk carrier, tanker and container.

CS: classification society. If the vessel is a member of International Association of Classification Societies (IACS), *CS=1*; otherwise *CS=0*

FS: flag state. If the vessel's flag is a close registry, *FS=1*; otherwise *FS=0*

Zj: dummy variables representing different geographical zones. In this thesis, we divide the world into 31 zones according to the *World Casualty Statistics*. Each zone has its own effect on the accident probability.

ε: Stochastic component that follows the logistic distribution, including objective causes (e.g. safety equipment, vessel structure) and subjective causes (e.g. ship owners' effort, crew ability and experience). In this study, it is used to refer to the maintenance quality of the vessel (e.g. substandard or standard). If the value is positive, the vessel is a substandard vessel; if the value if negative, the vessel is viewed as a standard vessel (Li, et al., 2014).

Among these variables, *VA* and *VS* are continuous variables, and need to be transformed into discrete variables. The classification has been clarified in section 7.2.2. *VT*, *CS*, *FS*, and *Zi* are all dummy and discrete variables.

Although the maritime accident case is a binary logistic regression (there are only two states for dependent variable *y*), the results obtained from multinomial regression can also fit this case because binary logistic regression is a special case of multinomial regression.

Through applying the Maximum Likelihood Estimator (MLE) method, the estimation of βi is achieved through SPSS software, which is shown in Table 6.4.

Table 6.4 Coefficients of the model

Variable	Variable label	Coefficient	p-value
β_0	Constant	-2.42	0.000
VA	Vessel age	-0.03	0.000
VS	Vessel size	0.09	0.000
VT1	Dry cargo	1.25	0.000
VT2	Bulker	0.50	0.000
VT3	Container	0.21	0.000
VT4	Tanker	0.00	0.000
VT5	Passenger	0.29	0.000
CS	Classification societies	-0.95	0.000
FS	Flag state	0.18	0.000
Z1	Zone1	0.49	0.000
Z2	Zone2	-0.21	0.003
Z3	Zone3	16.39	0.885
Z4	Zone4	-0.48	0.000
Z5	Zone5	-0.71	0.000
Z6	Zone6	2.61	0.000
Z7	Zone7	-0.71	0.000
Z8	Zone8	0.97	0.000
Z9	Zone9	0.78	0.000
Z10	Zone10	1.49	0.000
Z11	Zone11	-0.51	0.000
Z12	Zone12	-1.11	0.000
Z13	Zone13	-0.43	0.000
Z14	Zone14	16.75	0.912
Z15	Zone15	-0.17	0.185
Z16	Zone16	0.87	0.000
Z17	Zone17	16.49	0.950
Z18	Zone18	0.92	0.000
Z19	Zone19	0.46	0.000
Z20	Zone20	-0.60	0.000
Z21	Zone21	-1.62	0.000
Z22	Zone22	-1.71	0.000
Z23	Zone23	0.13	0.094
Z24	Zone24	1.37	0.000
Z25	Zone25	1.19	0.000
Z26	Zone26	16.93	0.893
Z27	Zone27	0.68	0.000
Z28	Zone28	2.71	0.000
Z29	Zone29	-0.75	0.000
Z30	Zone30	-1.89	0.000

(Source: Author)

Table 6.4 presents the information related to the estimation of the probability of the vessel being involved in a maritime accident, including the coefficient value and the partial effects of the coefficients. The results indicate that the model fits the data well. Almost all the variables are highly significant with the occurrence of maritime accidents, because the p-values are less than 0.01 (except several zones).

Eventually, by inserting the values of these coefficients into Equation (6-2), the accident rates of bulk carriers under different situations is obtained and presented in Table 6.5.

Table 6.5 The accident rate of bulk carriers under different situations

Ship safety condition	Standard											
VS	Smaller											
VA	Young				Average				Old			
FS	Closed		Open		Closed		Open		Closed		Open	
CS	Non-IACS	IACS	Non-IACS	IACS	Non-IACS	IACS	Non-IACS	IACS	Non-IACS	IACS	Non-IACS	IACS
Accident	0.12	0.07	0.13	0.09	0.1	0.05	0.14	0.07	0.08	0.04	0.09	0.04
Non-Accident	0.88	0.93	0.87	0.91	0.9	0.95	0.86	0.93	0.92	0.96	0.91	0.96
Ship safety condition	Standard											
VS	Larger											
VA	Young				Average				Old			
FS	Closed		Open		Closed		Open		Closed		Open	
CS	Non-IACS	IACS	Non-IACS	IACS	Non-IACS	IACS	Non-IACS	IACS	Non-IACS	IACS	Non-IACS	IACS
Accident	0.19	0.08	0.24	0.11	0.12	0.06	0.16	0.08	0.1	0.01	0.12	0.02
Non-Accident	0.81	0.92	0.76	0.89	0.88	0.94	0.84	0.92	0.9	0.99	0.88	0.98
Ship safety condition	Sub-Standard											
VS	Smaller											
VA	Young				Average				Old			
FS	Closed		Open		Closed		Open		Closed		Open	
CS	Non-IACS	IACS	Non-IACS	IACS	Non-IACS	IACS	Non-IACS	IACS	Non-IACS	IACS	Non-IACS	IACS
Accident	0.26	0.28	0.32	0.24	0.19	0.22	0.28	0.3	0.24	0.39	0.21	0.15
Non-Accident	0.74	0.72	0.68	0.76	0.81	0.78	0.72	0.7	0.76	0.61	0.79	0.85
Ship safety condition	Sub-Standard											
VS	Larger											
VA	Young				Average				Old			
FS	Closed		Open		Closed		Open		Closed		Open	
CS	Non-IACS	IACS	Non-IACS	IACS	Non-IACS	IACS	Non-IACS	IACS	Non-IACS	IACS	Non-IACS	IACS
Accident	0.35	0.2	0.41	0.2	0.29	0.16	0.28	0.19	0.2	0.39	0.27	0.18
Non-Accident	0.65	0.8	0.59	0.8	0.71	0.84	0.72	0.81	0.8	0.61	0.73	0.72

(Source: Author)

However, the classification of the situations in Table 6.5 is too detailed to put into the Nash solution to the game model, the accident rates in Table 6.5 need normalization[4]. Table 6.6 presents the result of normalization, which is useful for later calculation.

Table 6.6 Accident rates of bulk carriers

Vessel size	Small					
Vessel age	Young		Medium		Old	
SO's effort	Stan	Sub	Stan	Sub	Stan	Sub
Accident rate	0.106	0.278	0.0959	0.26	0.0643	0.227
Vessel size	Large					
Vessel age	Young		Medium		Old	
SO's effort	Stan	Sub	Stan	Sub	Stan	Sub
Accident rate	0.164	0.299	0.111	0.234	0.0669	0.249

(Source: Author)

6.2.4 Detention cost

Because of the detention punishment from the port authority, avoiding detention with minimum effort is the primary goal of the ship owner. At the same time, detention punishment also plays an important role in regularizing the behaviours of the ship owner from the port authority perspective. Hence, the detention cost (or the detention punishment) C_D is a focus for both sides.

If C_D is not large enough, the ship owner may maintain their vessels at a sub-standard safety level. In order to reduce the social welfare loss, the port authority have to increase the inspection rate or extend the detention time; if C_D is large enough, the ship owner will turn to improve the quality of vessels, resulting in lower inspection costs and a lower accident rate.

However, the data of detention cost is unavailable because it is an abstract parameter changing with different situations (i.e. different ports, different vessel type, and different regional policy) and there is no source providing related data. In order to illustrate how the model works, an assumption is made according to related academic research. Specifically, C_D is assumed in a linear relationship with the expected accident loss of sub-standard vessels, as

[4] Normalization means adjusting values measured on different scales to a notionally common scale, often prior to averaging.

the punishment policy aims at dealing with illegal actions and sub-standard safety levels of the inspected vessels (Li, et al., 2015).

$$C_D = \omega C_A P_m$$

Where ω represents the punishment intensity. It is a product of multiple influencing factors, especially detention time. A longer detention time means a severe punishment intensity to the vessel.

The setting of detention cost in this thesis is just for the calculation and analysis of Nash equilibrium solution, as well as illustrate how the proposed game model works. In practice, port authorities can set this parameter as a function of detention time according to historical statistics.

6.3 OPTIMAL INSPECTION RATE

As discussed in sections 6.1 and 6.2, all the parameters in Equation (5-8) are constant values, except the detention cost. The detention cost is a dynamic parameter that varies with the punishment intensity ω. That is to say, the optimal inspection rate is actually a function of the punishment severity ω, denoted as $X(\omega)$.

Because ω is a positive variable related to the port inspection regulations, it is impractical to fix it at a certain value to satisfy all the cases. Hence, in this study, the punishment severity is changed to see the optimal inspection rates in various circumstances.

The following Table 6.7 shows the optimal inspection rates when ω changes from 0 to 20 (ω is integer). The purpose is to see the variation of optimal inspection rate with different punishment intensity and analyse its trends.

Table 6.7 Optimal inspection rate with different punishment severity levels

	Small			Large		
	Young	Medium	Old	Young	Medium	Old
ω=1	65.025%	63.184%	64.793%	53.061%	55.913%	67.126%
ω=2	40.343%	39.316%	41.103%	31.518%	33.892%	42.716%
ω=3	29.243%	28.536%	30.098%	22.417%	24.315%	31.325%
ω=4	22.933%	22.396%	23.741%	17.394%	18.958%	24.730%
ω=5	18.863%	18.430%	19.602%	14.210%	15.536%	20.429%
ω=6	16.020%	15.657%	16.691%	12.011%	13.160%	17.403%
ω=7	13.921%	13.610%	14.533%	10.402%	11.414%	15.157%
ω=8	12.309%	12.036%	12.870%	9.173%	10.078%	13.425%
ω=9	11.031%	10.788%	11.548%	8.203%	9.021%	12.048%
ω=10	9.994%	9.775%	10.472%	7.419%	8.165%	10.927%
ω=11	9.135%	8.936%	9.580%	6.772%	7.457%	9.997%
ω=12	8.412%	8.229%	8.827%	6.229%	6.863%	9.213%
ω=13	7.795%	7.626%	8.185%	5.766%	6.356%	8.543%
ω=14	7.262%	7.106%	7.629%	5.367%	5.919%	7.964%
ω=15	6.798%	6.652%	7.144%	5.020%	5.538%	7.458%
ω=16	6.389%	6.252%	6.717%	4.715%	5.203%	7.013%
ω=17	6.027%	5.898%	6.339%	4.445%	4.906%	6.618%
ω=18	5.703%	5.581%	6.000%	4.205%	4.642%	6.265%
ω=19	5.413%	5.297%	5.696%	3.989%	4.404%	5.948%
ω=20	5.151%	5.041%	5.422%	3.794%	4.190%	5.661%

(Source: Author)

Based on the information in Table 6.7, Figure 6.3 provides a visualized diagram to describe the trend of optimal inspection rates when the punishment severity changes.

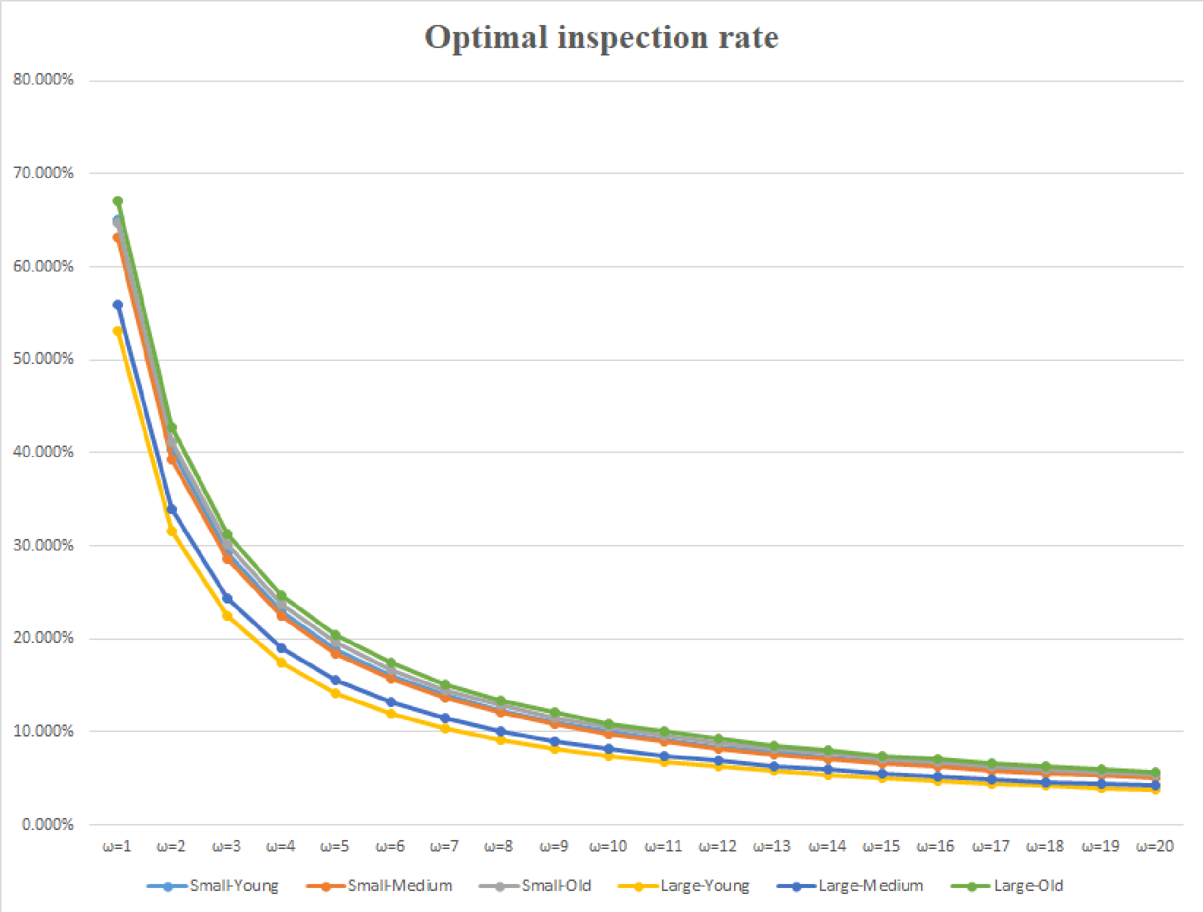

Figure 6.3 Trend of optimal inspection rate

(Source: Author)

From Table 6.7 and Figure 6.3, several conclusions are made and research implications are derived.

(1) With the increase of punishment severity, the optimal inspection rates see a decreasing trend regardless of the vessel conditions.

For example, the optimal inspection rate of small and young bulk carriers at $\omega=1$ is 65.025% and falls to 18.863% when ω increases to 5.

Actually, when calculating an optimal inspection rate, the only variable in Equation (5-8) is the severity degree ω. Other parameters, like the accident rate, accident loss, they are all constant. Hence, the function of optimal inspection rate can be written as

$$X(\omega) = \frac{a_3}{a_1\omega + a_2}$$

Where a_1, a_2, a_3 are positive constant.

Because of the positive value of ω, therefore, the first derivative test of the optimal inspection rate is

$$X'(\omega) = -\frac{a_1 a_3}{(a_1\omega + a_2)^2}$$

$X'(\omega) < 0$ means the optimal inspection rate is a decreasing function and does not have an extremum. The limiting case lies that when ω is infinitely great, the optimal inspection rate of bulk carriers is infinitely close to zero regardless of the safety condition and characteristics of the vessel.

(2) The declining speed of the optimal inspection rates slows down with the increase of the punishment severity.

It can be explained from a mathematical perspective.

The second derivative test of the optimal inspection rate is:

$$X''(\omega) = \frac{2{a_1}^2 a_3}{(a_1\omega + a_2)^3}$$

Because ω is a positive variable,

$$X''(\omega) > 0$$

If the second derivative test of a function is always positive no matter how the variable changes, the first derivative test is an increasing function. When combining it with the result that $X'(\omega) < 0$, we disclose that $X'(\omega)$ is a negative increasing function, and $|X'(\omega)|$ is a positive decreasing function.

When represented in the graph, $X'(\omega)$ reflects the slope of the line $X\ (\omega)$, and $|X'(\omega)|$ measures the steepness or grade of the line.

Therefore, a positive decreasing nature of $|X'(\omega)|$ indicates the line of optimal inspection rate is steeper at first and tends to be smooth with the increase of the punishment severity.

In fact, the variation trend reveals that with the increase of the punishment intensity, the standard ship owners' motivation of implementing better safety maintenance policy among the sub-standard ship owners becomes lower and lower.

(3) Vessel age has little influence on the optimal inspection rates of small bulk carriers.

Table 6.8 illustrates the standard deviation of small bulk carriers. The standard deviation here represents the variation of the optimal inspection rates of small bulk carriers. It is obvious to find that the standard deviation of small bulk carriers is always low no matter how the punishment intensity changes. It means that the dispersion of the data is kept at a low level under all circumstances. In addition, the value of standard deviation is always below 1%, and keeps dropping when the punishment intensity increases. Hence, for small bulk carriers, vessel age has no influence on the optimal inspection rates.

Table 6.8 The standard deviation of small bulk carriers

Small				
	Young	Medium	Old	Standard deviation
$\omega=1$	65.03%	63.18%	64.79%	0.82%
$\omega=2$	40.34%	39.32%	41.10%	0.73%
$\omega=3$	29.24%	28.54%	30.10%	0.64%
$\omega=4$	22.93%	22.40%	23.74%	0.55%
$\omega=5$	18.86%	18.43%	19.60%	0.48%
$\omega=6$	16.02%	15.66%	16.69%	0.43%
$\omega=7$	13.92%	13.61%	14.53%	0.38%
$\omega=8$	12.31%	12.04%	12.87%	0.35%
$\omega=9$	11.03%	10.79%	11.55%	0.32%
$\omega=10$	9.99%	9.78%	10.47%	0.29%
$\omega=11$	9.14%	8.94%	9.58%	0.27%
$\omega=12$	8.41%	8.23%	8.83%	0.25%
$\omega=13$	7.80%	7.63%	8.19%	0.23%
$\omega=14$	7.26%	7.11%	7.63%	0.22%
$\omega=15$	6.80%	6.65%	7.14%	0.21%
$\omega=16$	6.39%	6.25%	6.72%	0.20%
$\omega=17$	6.03%	5.90%	6.34%	0.19%
$\omega=18$	5.70%	5.58%	6.00%	0.18%
$\omega=19$	5.41%	5.30%	5.70%	0.17%
$\omega=20$	5.15%	5.04%	5.42%	0.16%

(Source: Author)

(4) Large and old bulk carriers have the highest optimal inspection rates. In addition, old vessels are always the most risky vessels.

In Figure 6.3, the curve representing the optimal inspection rate of 'Large-old bulk carriers' is always on top of other vessel types no matter how the punishment intensity changes, followed closely by the curve 'Small-Old bulk carriers'. As a summary, old vessels have higher optimal inspection rates than young and average vessels when other variables remain identical. The finding derived from the empirical study conforms to the common sense that old vessels are more risky. The components of most old vessels are more fragile and may not able to tackle emergencies and accidents when sailing. Meanwhile, the maintenance cost spent on old vessels is a huge number compared to other vessels as indicated in Table 6.2, restraining the motivation of many ship owners.

Hence, a higher optimal inspection rate for old bulk carriers reflects the hazards and risks that old vessels possess, prompting the port authority to pay more attention to them and prevent illegal actions from ship owners.

(5) For young and medium bulk carriers, vessel size is a factor of more influential power than vessel age in PSC.

To compare the effect of vessel size and vessel age on the optimal inspection rate, sensitivity analysis is conducted. When locking one factor and changing the states of another factor (target factor), the change of optimal inspection rate is measured as the effect of the target factor under this scenario.

For example, when $\omega=1$, if the vessel is a small vessel, it can be observed that the optimal rate of a young small vessel is 65.03%. On the other hand, the medium small vessel is 63.184%. Therefore, the different value 1.84% is the effect of vessel age on the optimal inspection rate when locking vessel size at 'small' and $\omega=1$. Table 6.9 shows the individual effect of vessel size and vessel age under different scenarios.

Table 6.9 Effect of vessel age and vessel size

Target factor	Vessel age		Vessel size	
Locked state	Small	Large	Young	Old
$\omega=1$	1.84%	2.85%	11.96%	7.27%
$\omega=2$	1.03%	2.37%	8.83%	5.42%
$\omega=3$	0.71%	1.90%	6.83%	4.22%
$\omega=4$	0.54%	1.56%	5.54%	3.44%
$\omega=5$	0.43%	1.33%	4.65%	2.89%
$\omega=6$	0.36%	1.15%	4.01%	2.50%
$\omega=7$	0.31%	1.01%	3.52%	2.20%
$\omega=8$	0.27%	0.90%	3.14%	1.96%
$\omega=9$	0.24%	0.82%	2.83%	1.77%
$\omega=10$	0.22%	0.75%	2.58%	1.61%
$\omega=11$	0.20%	0.68%	2.36%	1.48%
$\omega=12$	0.18%	0.63%	2.18%	1.37%
$\omega=13$	0.17%	0.59%	2.03%	1.27%
$\omega=14$	0.16%	0.55%	1.90%	1.19%
$\omega=15$	0.15%	0.52%	1.78%	1.11%
$\omega=16$	0.14%	0.49%	1.67%	1.05%
$\omega=17$	0.13%	0.46%	1.58%	0.99%
$\omega=18$	0.12%	0.44%	1.50%	0.94%
$\omega=19$	0.12%	0.42%	1.42%	0.89%
$\omega=20$	0.11%	0.40%	1.36%	0.85%

(Source: Author)

It is obvious that vessel size has more influence on the inspection rate than vessel age under various situations. However, the tendency of the impact magnitude gradually decreases when the punishment intensity of the port authority is higher and higher.

6.4 RECOMMENDATIONS FOR PORT AUTHORITIES

6.4.1 Suggestions when formulating inspection policy

This section illustrates how the proposed model and theoretical optimal inspection rates can help port authorities to make their optimal decisions in PSC inspections. It is noteworthy that the prerequisite of the suggestion is that port authorities and ship owners make their decisions independently, and both of them are not aware of the choice of the other.

When applying the optimal inspection policy in practice, the social welfare increase (detention cost) assumption in the game model should be improved first. Based on the historical inspection data of the port, the social welfare loss (detention cost) can be set as a function of detention time, which is denoted as:

$$C_D = DTi * C_i^0 \tag{6-4}$$

Where DT_i is detention time (day) and represents the punishment intensity, while C_i^0 is the detention cost of vessel type i per day. Here vessel types are classified according to the inspection performance, and the vessels of same type will have the same detention time.

Next, the port authority should figure out the average detention time of different vessel types under different scenarios, and then calculate the possible social welfare increase (detention cost) per inspection based on Equation (6-4)

Based on the proposed optimal inspection rate equation, the optimal inspection rates of vessels under different conditions can be obtained when inserting corresponding values, denoted as X_i (i represents vessel types). Meanwhile, the historical data can tell the numbers of bulk carriers arriving at port per day, denoted as N_i. Therefore, the optimal number of PSC inspections at the port per vessel type per day is X_i N_i, which is useful for the port authority when formulating its inspection regulations.

However, sometimes the resources that the port authority has in reality do not support them to do the exactly number of inspections that the Nash solution suggests. On this occasion, the port authority has two strategies:

1) Increase the resources for PSC inspection, e.g. PSC inspectors (human resources), funding and operational expenditure.

2) If it is not possible to increase the resources, the port authority can use the Equation (5-8) and (6-4) to improve its inspection policy.

- Based on the limited resources the port authority has for different vessel types, the maximum number of inspections on different vessel types per day is obtained. Hence, the required optimal inspection rates are calculated, which is denoted as $X_i^{'}$
- Input $X_i^{'}$ into optimal inspection rate Equation (5-8) and use the backward calculation to get the detention cost $C_{Di}^{'}$ for different vessel types.
- Once the required detention cost $C_{Di}^{'}$ is obtained, the punishment intensity and the detention time of different vessel types $DT^{'}_i$ can be calculated through Equation (6-4). Because $X_i^{'} < X_i$, then $C_{Di}^{'} > C_{Di}$, $DT^{'}_i > DT_i$. The port authority can prolong the detention time and increase the punishment intensity to the corresponding level based on the optimal inspection equation to ensure the operation of PSC inspection system.

In general, when a port authority has sufficient resources, it should choose the optimal inspection rate; otherwise it can increase the punishment intensity level to tackle the sub-standard effort and illegal actions of the ship owner.

6.4.2 The decision-making framework for the port authority

Since NIR was implemented, the Paris MoU continued with its work of improving the performance of the PSC inspection system and inspecting vessels in accordance with the relevant instruments of the Memorandum. Over the years within the Paris MoU, the developments and works carried out by the authority were apparent, for example, the Concentrated Inspection Campaign (CIC), the updated ‘white, grey, black’ list every year, the development of the Technical Evaluation Group, the training and development of PSCOs, the detention review panel, and vessel quality management. These actions enable port authorities to execute high quality and detailed PSC inspections, and improve the efficiency and accuracy of the inspection results.

In this regard, this section aims to propose a decision-making framework for port authorities when formulating the inspection policy and examining the inspected vessels to fit the increasingly perfect inspection system. Due to the money, human resources, and other types of cost that are consumed, it is of vital importance to provide an optimal decision-making framework for port authorities when inspecting vessels. It can be achieved by incorporating the BN model of Post-NIR PSC inspection system and the non-cooperative strategic game proposed in this research. The results yielded by the framework present a novel way to select the best actions under different situations, which enables decision makers to find optimal solutions to improve performance of the PSC inspection system.

The following Figure 6.4 describes the process of the proposed decision-making framework by this thesis. The improvements to the current practice have been highlighted in the figure and the detailed information is highlighted in the description of the framework as well.

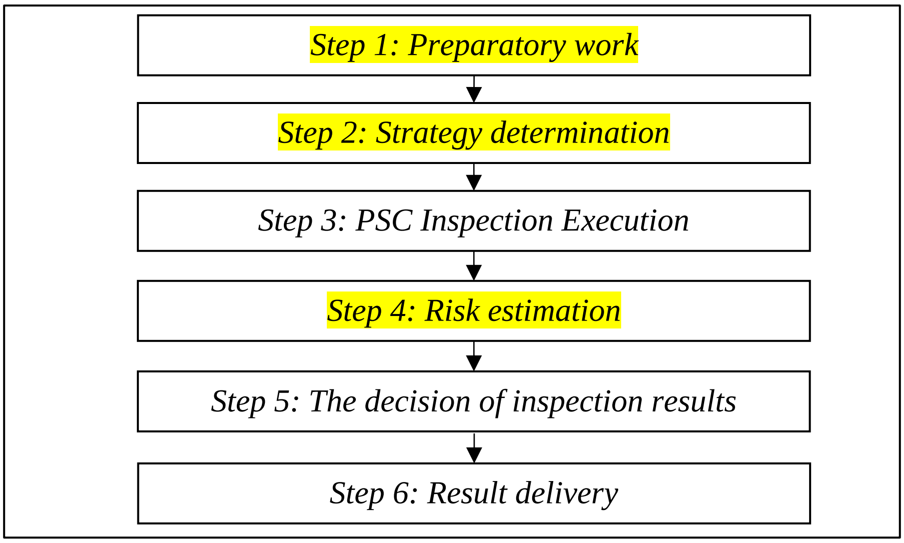

Figure 6.4 Decision-making framework for the port authority

(Source: Author)

1) Preparatory work

The first step is preparatory work. *The port authority should collect and summarize the related information and statistics required for the modelling*, for example, the average detention time of detained bulk carriers under different scenarios, the possible social welfare increase (detention loss to the ship owner) per inspection, the numbers of bulk carriers arriving at port per day, the human resources (mainly PSCOs) it has, the limit of expenditure per day, etc. The statistic derived from historical records corresponds to the important elements in risk assessment BN model and strategic game model. *Clarifying the statistics in these aspects is essential for the later optimal inspection policy selection and decision-making process*.

2) Strategy determination

Based on the proposed optimal inspection rate derived from the game model, the port authority can choose the proper inspection strategy (the total number of inspections for different types of vessels) according to the resources it has. As discussed in section 7.4.1, if the port authority has enough resources, it should set the number of inspections per day according to the optimal inspection rate; if the port authority does not have enough resources, it should either acquire more resources to satisfy the optimal inspection rate or increase the punishment intensity to the corresponding level based on the existing resources. The strategy choice relies on the environment around the port and the overall situation of the PSC inspection system at this port. Once the strategy of number of inspections is determined, the port authority can pick the vessels based on the result of the last inspection, SRP of the vessel, selection regime of the port, and other factors.

3) PSC inspection execution

The next step is to carry out inspections on selected vessels. The ship owner has to report 24 hours before his/her vessel arrives at the port or anchorage of the Paris MoU region or before leaving the previous port or anchorage if the voyage is expected to take less than 24 hours. The report mission is obligated for all vessels that plan to berth at the port. In the report, some information is acquired to provide to the port authority, including ship identification, port of destination, estimated time of arrival, estimated time of departure, planned duration of the call, date of last expanded inspection in the Paris MoU region, etc. The port authority can decide whether to inspect the vessel based on the provided information, the historical inspection records, and the inspection strategy determined via optimal inspection rate.

The inspection will normally start with, as a minimum and to the extent applicable, examination of the documents in accordance with Annex 10 of the Paris MOU. In addition, the PSCO will conduct a general inspection of several areas on board to verify that the overall condition of the ship complies with that required by the various certificates.

If the ship is found to comply, the PSCO will issue a ‘clean’ inspection report (Form A) to the master of the ship. In case deficiencies have been identified, the inspection report will include a deficiencies found report (Form B) indicating any follow-up actions to be taken to rectify the deficiencies indicated. Next, the data of the respective ship and the inspection result will be recorded on the central computer database, located in Lisbon, Portugal.

Furthermore, control on compliance with on-board operational requirements may be included in the control procedures, particularly if the PSCO has reason to believe that the crew demonstrates insufficient proficiency in that area.

4) Decision of inspection results

When the inspection on board is completed, the port authority should decide whether to detain the vessel. In the current practice, the detention of a vessel is based on the professional judgment of PSCOs. Normally, the ship will be detained if the deficiencies on a ship are sufficiently serious to merit a PSCO returning to the ship to be satisfied that they have been rectified before the ship sails. However, this process is highly relied on the ability and experience of the PSCOs, and port authorities have to invest a lot to train professional PSCOs, otherwise the results may not reliable.

Under the new decision-making framework in this thesis, this process can be done through the proposed BN model. The port authority can apply the 'Post-NIR' BN model to estimate the detention rate of this vessel. Through comparing the detention rate of this vessel with the average detention rate of this particular vessel type, those vessels having an abnormally high detention rate should be detained. On the contrary, the vessels that have low detention rate are standard and high quality vessels, being assumed to pass the inspection with no doubt.

Therefore, the application of BN model not only eases the burden of port authorities on training professional PSCOs, but also reduce the pressure of PSCOs on providing reliable inspection results.

In addition, when the port authority decides to detain the vessel, it needs to set the period of detention for the vessel. There are a large number of factors influencing the detention time, for instance, the number of detainable deficiencies, the severity level of the deficiencies, the complexity of the repair, the place for repair at the port, etc. The port authority has its own system and principles to determine the detention period for the sub-standard vessels.

Additionally, if the vessel is detained for multiple detentions, the vessel will be banned. The vessel is not allowed to access any port in the region of the Paris MoU for a minimum period. Normally, the number of detentions is three in three years. The duration for first ban is up to 3 months, the second is 12 months, and the third ban would be 24 months or even a permanent ban.

6) Result delivery

Once the result of the inspection is determined, the PSCO will issue a notice of detention to the ship owner. Meanwhile, the PSCO will inform the ship owner that they have the right of appeal. The ship owner can choose to appeal to the coastal country, the flag state, or the RO. The flag state or RO may then ask the port authority to reconsider its decision to detain the vessel. If the outcome of the investigation and appeal is not satisfied, the flag state or the RO can send a request for review to the Paris MoU secretariat.

The following Table 6.10 summarize the improvements on the current PSC inspection practice of this thesis.

Table 6.10 Improvements on PSC practice

Stage	Improvements
Step 1: Preparatory work	➢ Collect and clarify the related information and statistics to provide a better foundation for inspection policy decisions
Step 2: Strategy determination	➢ The port authority can choose the optimal inspection strategy, i.e. the number of inspections for each type of vessels under various situations, based on the resources it has through the calculation of optimal inspection rate calculation.
Step 4: Decision of inspection results	➢ The proposed BN model can help port authority to estimate the detention rate and decide the inspection results from a more convenient and easier way than the current mechanism. ➢ No heavy burden on PSCOs under the new framework. ➢ The cost on PSC training are reduced.

6.5 CONCLUSIONS

This chapter has conducted an empirical study to analyse the theoretical optimal inspection rates obtained in Chapter 5. The result reveals the optimal inspection rates of bulk carriers under different conditions from a port authority viewpoint. New managerial insights are established and verified through an empirical study investigating the inspections happened in 2015-2017. For example, 1) with the increase of punishment severity, the optimal inspection rates present a decreasing trend regardless the vessel conditions. 2) The declining speed of the optimal inspection rates slows down with the increase of the punishment severity level. 3) Vessel age has little influence on the optimal inspection rates of small bulk carriers. 4) Large and old bulk carriers have the highest inspection rates. 5) For young and medium bulk carriers, vessel size is a factor of more influential power than vessel age in PSC. The above managerial insights can be served as useful information for i) the port authorities when formulating their inspection policy regarding the bulk carrier part and ii) the ship owners when minimizing their ships detention rate given economic constrains.

Based on the findings, there are two suggestions for port authorities when formulating their inspection policies respectively:

- If having sufficient resources for inspection, the port authority can use the calculated optimal inspection rate to determine the number of inspected bulk carriers per day.
- If there are limited inspection resources, port authorities can use the backward calculation function to increase the vessel detention time based on the maximum number of inspections it can afford per day.

Meanwhile, a decision-making framework consisting of six steps is proposed to help port authorities make decisions during an inspection. The framework incorporates the risk assessment BN model and the strategic game model developed in this research, thus making the framework more reliable and convincing.

Further effort will focus on the improvement of the game model, taking into account the effect of repair at port due to detention, the severity classification of accidents and corresponding accident loss. Data acquisition (i.e. the statistics of total accident loss) presents another issue to investigate in the future research agenda.

CHAPTER 7 SUMMARY AND DISCUSSIONS

In this chapter, the proposed models and techniques described in Chapter 3, 4, 5, and 6 are briefly summarised and discussed to make a comprehensive demonstration on the influence of the new inspection regime of PSC and the optimal decisions of port authorities under current conditions. Additionally, the research contributions of this study are revealed, as well as the suggestions on the further improvements of the research topic.

7.1 RESEARCH IMPLICATION

The much-anticipated New Inspection Regime implemented by Paris MoU transformed and modernised the PSC inspection system a lot, making it more and more important in preventing illegal actions of ship owners and ensuring maritime safety, and even become the last line of defence against sub-standard vessels. Despite the fact that new PSC inspection system came into force for many years, the emergence of sub-standard increased gradually. In fact, a decision-making framework is required to help port authorities to make optimal decisions when executing PSC inspections to deal with the potential risks of sub-standard vessels. However, findings from the literature have revealed that there are few works focusing this topic. Thus, this thesis incorporates the risk assessment tool and the analytical tool to propose a decision-making framework for port authorities under various situations in new PSC inspection system.

The research objectives are achieved through three technical parts (because Chapter 6 utilises a case study to illustrate the game model in Chapter 5, hence these two chapters are viewed as a whole part), which is discussed in detail as follows. Meanwhile, the research questions put forward in Chapter 1 are also solved.

7.1.1 Discussions of the advanced risk assessment model for PSC inspections under NIR using data-driven BN approach

In Chapter 3, a prediction tool to help port authorities estimate the detention rate under different situations since the implementation of NIR is developed. During the process of developing risk prediction tool, Q1 and Q2 proposed in Research question part are solved.

In addition, this chapter also reveals the degree of importance of different risk factors influencing PSC inspection results in different periods, i.e. vessel flag, vessel age, DWT for

‘Pre-NIR’ period, company performance, and inspection date for ‘Post-NIR’ period. The work was assessed and completed by data-driven Bayesian network approach. The data-driven Bayesian network approach is a combination of data-driven approach (in this study, TAN learning) and the original BN model to induce the risk assessment model through data, not expert judgment. This approach is an advanced version of the original BN approach that aims to reduce the dependence on human experts and improve the model accuracy. Among the various data-driven approaches, TAN learning shows its superiority to deal with the construction and learning problem in BN because of its accuracy and competitiveness.

In this part, two BN models are developed through TAN learning, one is a ‘Pre-NIR’ BN model (before the implementation of NIR), the other is a ‘Post-NIR’ model (after the implementation of NIR). The purpose of setting two BN models is to display the conditions of different periods, which is of vital importance for the later analysis of the influence of NIR on the PSC inspection system.

Different from the traditional BN construction process, a new conceptual methodology to construct the PSC inspection model is developed including the following steps in this study.

1) Data acquisition.

A dataset containing 72,785 inspection records from 2005-2008 and 49,328 inspection records from 2015-2017 extracted from the Paris MoU online inspection system is established. As one of the popular vessel types, bulk carriers account for 15% of the total number of PSC inspections, and are thus selected as the research target in this study.

2) Variables identification – Answer to Q1

The risk variables identified from inspection records are explained with particular reference to their state definitions in Chapter 3. For Pre-NIR period, vessel flag, vessel age, DWT, RO, inspection type, inspection port and number of deficiencies are the factors that may influence detention; for post-NIR period, vessel flag, vessel age, company performance, inspection type, inspection port, inspection date and number of deficiencies are the identified ones.

3) Data-driven network construction – Answer to Q2

According to the TAN learning, the original data-driven networks for PSC inspections are constructed. However, the CPT table would be too large to have enough sampling information in the inspection database for the calculation of conditional probabilities. To solve this issue, divorcing approach is utilized and two mediating dummy variables, ‘vessel group’ and ‘inspection group’, are introduced. Meanwhile, some meaningless and incorrect links in the network are modified. Figure 3.6 to Figure 3.10 describe the process of improving the structure of the BN.

4) CPT calculation

Equation (3-2) and Equation (3-3) provide a way to calculate the conditional probabilities, which is known as the gradient descent approach. This three-step calculation process is a quantitative approach and the results are shown in Table 3.1 to Table 3.7. Meanwhile, the whole information of CPT can be found in Appendix 1 and Appendix 2.

5) Model result

Figure 3.10 and Figure 3.13 present the final model of ‘Pre-NIR’ period and ‘Post-NIR’ period, respectively. The detention rate in general situations estimated by theoretical models is in line with the direct calculation from the inspection database.

The final model proposed in this chapter, Figure 3.13, can be served as the prediction tool for port authorities under different conditions since NIR is implemented. Through several real inspection cases, this prediction tool is proved to have practical significance for port authorities. When a bulk carrier arrives at a port, the port authority can use the proposed prediction tool first to conduct a primary screening. If the result is positive, the port can devote less effort and resources to it; if the result is negative, the vessel is a high-risk vessel and shall be examined carefully under the new inspection system.

Through the TRI sensitivity analysis, the degree of importance of risk variables are listed (Answer to Q2)

Inspection group > Number of deficiencies > Type of inspection > Vessel group > RO > Vessel age (Pre-NIR)

Number of deficiencies > Inspection group > Vessel group > Company performance > Vessel age > Type of inspection (Post-NIR)

As ‘inspection group’ and ‘vessel group’ are class variables which do not exist in PSC inspection records, ‘Number of deficiencies’ is in fact the most important risk factor, no matter before or after the implementation of NIR. This result indicates sub-standard performance of inspection-related items (Number of deficiencies, type of inspection, etc.) is more likely to lead to detention than unqualified intrinsic attributes of vessels (vessel age, dwt, RO, etc.).

The novelty of this chapter lies in two aspects, 1) construct a data-driven BN for risk analysis and prediction on PSC system for the first time; 2) take company performance into account when constructing the risk assessment model for 'Post-NIR' period. Further, when analysing the optimal inspection policy for port authorities after the implementation of NIR in Chapter 5, the results of BN play a crucial role in the game model construction.

7.1.2 Discussions of the influence of the implementation of NIR on PSC inspection system

Since NIR was implemented in 2011, its influence on the PSC inspection system and inspection results is still not clarified in academia. Chapter 4 conducts an analysis to figure out the influence of the implementation of NIR on PSC inspection system from both the micro-level and macro-level perspectives (Answer to Q3). The statistics and information used in this chapter come from two sources: one is the results from two proposed BN models in Chapter 3; the other is the facts & figures collected from the Paris MoU annual reports in 2005-2017.

Based on the statistics derived from official annual reports, the changes of PSC inspection system from the macro-level perspective are clarified from different aspects. Some important and positive findings are presented as follows.

1) From 2011, the number of inspections and individual inspected vessels continued to drop, except 2014, when both indicators increased slightly.

2) Since NIR was implemented, both the number of inspections and the inspected vessels per year remained stable compared to the former inspection system.

3) The introduction of NIR significantly reduced the deficiency rate and detainable deficiency rate in the Paris MoU inspection system.

4) Since NIR was implemented, the deficiency rate maintained a downward trend, from 2.662 in 2011 to 2.346 in 2016, especially in 2014, where there was a huge decline.

5) The detention rate after 2011 was lower and more stable compared to the period before NIR.

6) The implementation of NIR significantly reduced the burden on the ship owners (from 1.6 inspections/year to 1.2 inspections/year).

7) The implementation of NIR reduced the number of inspections of most vessel types, and kept this number at a steady level.

8) The detention rate of all vessel types dropped, indicating the positive influence on detention rate of NIR suited for the major vessel types in the PSC inspection system.

It is obvious to find that the changes brought by NIR are almost positive, indicating the introduction of NIR indeed transforms the PSC inspection system to a large extent and is no doubt the biggest change in PSC history.

Another perspective lies in the micro-level analysis. Based on the proposed models in Chapter 3 and the corresponding results, the influence of NIR is explained in four aspects: the change of influence degree of risk factors in different periods, the impact of the new risk factor 'company performance', the prior probability change, and the role change of two factor groups. The changes in these aspects are described in detail in section 4.4. Most of the changes are also positive like the macro-level analysis.

1) Since NIR was implemented, the relationships between risk factors and the inspection results have become closer and stronger.

2) Vessel-related risk factors have been paid more attention since the implementation of NIR.

3) The newly added factor, company performance, is viewed as an important risk factor that greatly affects the final inspection results. The vessels under high and medium company management are highly unlikely to be detained; on the other hand, low and very low ISM companies are on the 'black list' of all ports within the range of the Paris MoU and have greatly increased chances of detention.

4) The attitudes of port authorities towards vessels under the management of low and very low shipping companies are rigorous, much more than the benefits gained from selecting a high/medium management company for inspection.

5) The flag performance of inspected vessels improves a lot and almost all the inspected vessels have a white list flag.

6) The age of inspected vessels from 2011 is becoming younger, indicating the implementation of NIR eliminated those low quality old vessels.

7) Compared to the previous system, both the high inspection risk and high vessel risk vessels will have much higher chances to be detained by port authorities under the new inspection system.

8) Vessels having low vessel-related risks will have a huge reduction in the detention rate when accepting inspections, stimulating the ship owners to be more concerned about the vessel quality.

9) Vessel-related risks are no longer an indifferent part compared to inspection-related risks and gradually become crucial to the inspection results.

10) Port authorities are vigilant to all potential risks and will no longer tolerate any types of risk

Generally speaking, the findings and changes brought by NIR provide important insights for port authorities and ship owners to understand the improvements of the inspection system, e.g. the change of preferred inspection types; the more rigid policy against sub-standard vessels. All the signs indicate that NIR has taken port state control to the next level.

Overall, this chapter displays the influences and changes that the New Inspection Regime gave to the whole PSC inspection system for the first time. Since NIR was introduced, the Paris MoU has invested many resources to maintain and improve this regime, as well as propagandize and generalize this system to the whole world. Through the analysis of the related statistics since 2011 and the risk assessment models of the Paris MoU inspection system, it is simple to find the NIR was highly praised because it indeed brought many positive changes and improved the inspection system a lot. Based on this regime, the potential maritime risks related to vessel safety are very likely to be detected when the vessel is undergoing inspection at ports.

7.1.3 Discussions of the optimal inspection policy of port authorities after the implementation of NIR using risk-based game model

Under the new PSC inspection regime, one big issue for port authorities is to determine their inspection policies. Because of the resources and conditions, an optimal inspection policy is of vital importance for port authorities to ensure vessel quality and motivate ship owners. Meanwhile, due to the introduction of the company performance index, the ISM Company also need to regulate the quality of the vessels under their management now, hence it has become an important factor that may influence the inspection decisions of port authorities and ship owners in the current inspection regime. In Chapter 5 and Chapter 6, game theory is applied to figure out this issue. Combined with the results from the BN, a PSC inspection game model under NIR is constructed to clarify the optimal inspection policies for port authorities, aiming to provide important insights for coastal countries to deal with illegal ship owners and ISM companies. Research questions Q4, Q5 and Q6 are clarified.

When constructing the game model, several assumptions are made at first, for example, the players in the game (port authorities and ship owners) are rational, the vessels are classified into standard vessel and sub-standard vessel, the accident losses of the vessel with different maintenance effort are the same, and some basic assumptions of the strategic game. According to the definition of the strategic game, the parameters in the game model are identified from three aspects: players, strategies, and payoffs. It is obvious that there are two players, port authorities and ship owners, in the game. The former stakeholder can decide whether to inspect the vessel or not, while the latter can choose high or low maintenance effort on their vessels. As the most important component to form a game, the payoffs of different players in an inspection game are different. For ship owners, the payoffs consist of expected detention cost, expected accident loss, inspection cost, and other related costs, while for port authorities, the social welfare increase and loss, port charges, and other related costs are important parts. In this two-player non-cooperative strategic inspection game, the payoffs under each scenario (or strategic profile) is presented in the payoff matrix in Table 5.3, which describes the relationships between port authorities and ship owners under NIR (Answer to Q4). Mixed strategy Nash equilibrium solution for the game model is presented as shown in Equation (5-8) and Equation (5-9), which is known as the optimal inspection rate for the port authorities provided by the game model.

With the help of the results from the BN, the risks and uncertainties hidden behind the inspection games are quantified, which is denoted as the ‘detention rate’ in the game model and Nash solution (Answer to Q5). Table 6.7 and Figure 6.3 presents the optimal inspection rate under different conditions. The analysis of the results reveals several research implications:

1) With the increase of punishment severity, the optimal inspection rates experience a decreasing trend whatever the vessel condition.

2) The declining speed of the optimal inspection rates slows down with the increase of the punishment severity.

3) Vessel age has little influence on the optimal inspection rates of small bulk carriers.

4) Large and old bulk carriers have the highest optimal inspection rates.

5) For young and medium bulk carriers, vessel size is a factor of more influential power than vessel age in PSC.

In fact, when formulating the inspection policy, port authorities can use the proposed game model and optimal inspection rate formulation for reference. If they have enough resources for inspection, the port authority can use the optimal inspection rate to determine the number of inspected bulk carriers per day. If there are limited inspection resources, the port authority can use the backward calculation function of the proposed solution to improve its policy (increase the detention time for the vessel) based on the maximum number of inspections it can afford per day.

In addition, based on the 'Post-NIR' BN model and strategic game model proposed in this research project, a novel framework is developed for port authorities when making decisions during PSC inspections. The decision-making framework can act as an instruction for port authorities to improve the performance of PSC inspection system, and then ensure the vessel quality and maritime safety under NIR. (Answer to Q6)

Overall, this chapter provides some useful suggestions for port authorities to make decisions under the new PSC inspection system. The optimal inspection rate provided by the game model can provide important insights for port authorities to regulate illegal ship owners and sub-standard vessels. With an eye to the performance of ISM companies, the game model proposed in this chapter combines the results of BN, which highlights the novelty of this chapter.

The following table describes how the research questions of this thesis is solved.

Table 7.1 Solve of Research questions

Q1	Variable identification through PSC inspection records (Section 3.2.2)
Q2	The relationships between risk variables and inspection results are presented as the structure of BN models. (Section 3.3.3 & Section 3.4.3); The influencing degree of risk variables on inspection results is obtained via sensitivity analysis of the BN models. (Section 3.3.6 & Section 3.4.6)
Q3	The influence of NIR on PSC inspection system is clarified through a comparison analysis between 'Pre-NIR' period and 'Post-NIR' period. (Chapter 4)
Q4	The relationship between port authorities and ship owners is demonstrated in section 5.1 and illustrated in detail in section 5.3.3.
Q5	The risks and uncertainties hidden behind the inspection game is quantified through the prediction function of BN, presented as the detention rate under different situations. (Section 6.2.1)
Q6	Through incorporating the risk prediction tool (BN) and the optimal inspection policy (game model), a new conceptual decision-making framework is proposed to improve the current PSC inspection practice and overcome its deficiencies. It is useful for port authorities to make optimal decisions currently. (Section 6.4)

7.2 RESEARCH CONTRIBUTION

This study develops a novel methodology incorporating BN and game theory to provide a dynamic prediction tool for port authorities and ship owners, analyse the impact of the implementation of NIR on PSC inspection, as well as help port authorities to make decisions when regulating inspection policy. Through six chapters' work, the objectives are achieved and several contributions are made not only to academia, but also to the maritime industry.

1) The factors influencing the inspection results in PSC inspections in two periods (Pre-NIR period and Post-NIR period) are identified. Meanwhile, the degree of importance of major risk factors are listed based on the analysis on the proposed BN models.

2) Two BN models reflecting the inspection conditions are proposed based on the data collected from the Paris MoU online inspection system. The Post-NIR BN model can serve as a prediction tool for port authorities to estimate the detention rate of individual vessels under different situations within new inspection system.

3) The influence of NIR on the Paris MoU PSC system is clarified from two perspectives: micro-level and macro-level. Both perspectives prove that the implementation of NIR have positive influence on the whole PSC system, and NIR has definitely transformed the PSC inspection system and brought it to the next level.

4) Combined with the BN, a novel game model is proposed to illustrate the game relationship between ship owners and port authorities under NIR. Taking company performance into consideration, the mixed strategy Nash equilibrium solution proposes a theoretical optimal inspection rate for port authorities, aiming to provide important insights for port authorities when regulating inspection policy in the current situation.

5) Several suggestions are made to port authorities after analysing the optimal inspection rate generated from an empirical study. It is proved that the proposed optimal inspection rate has important practical significance.

6) A decision-making framework is proposed to help port authorities when making decisions in PSC inspections.

7.3 FURTHER IMPROVEMENTS

To improve the study, further work should focus on the following aspects:

1) When constructing the risk assessment model for PSC inspections, the severity of the punishment should be considered as an important node, which is represented by 'detention time' in inspection records. The introduction of this new node can enrich the model and help the industry to understand the current condition of the punishment on sub-standard vessels.

2) The improvement of the game model. Several factors and parameters should be taken into account when building the game model, for example, the effect of repair at port due to detention, on the accident rate, the severity classification of accidents and corresponding accident losses.

3) Data acquisition work. More statistics related to PSC inspections and maritime accidents need to be collected to fulfil the validation and the case study of the model, i.e. the total accident loss, and the updated maintenance cost.

4) The research targets can extend and not be restricted to bulk carrier. A comparison between the results of different vessel types can reveal their risk grades.

5) Nash equilibrium solution is a basic solution to the game model. More solution types are encouraged to provide more accurate and practical optimal inspection rates for port authorities, i.e. Stackelberg equilibrium solution.

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APPENDICES

Appendix One Conditional Probability Table of 'Pre-NIR' BN model

Table Appendix 1.1. CPT of 'Vessel group'

Vessel age	Vessel flag	RO	DWT	Low Detention Risk	High Detention Risk
Over20Y	Black High	High	Capesize	0.506161	0.493839
Over20Y	Black High	High	Handymax	0.436418	0.563582
Over20Y	Black High	High	Handysize	0.001225	0.998775
Over20Y	Black High	High	Panamax	0.510926	0.489074
Over20Y	Black High	High	Small	0.001377	0.998622
Over20Y	Black High	Low	Capesize	0.544272	0.455728
Over20Y	Black High	Low	Handymax	0.474572	0.525428
Over20Y	Black High	Low	Handysize	0.559007	0.440993
Over20Y	Black High	Low	Panamax	0.481589	0.518411
Over20Y	Black High	Low	Small	0.001343	0.998657
Over20Y	Black High	Medium	Capesize	0.477040	0.522960
Over20Y	Black High	Medium	Handymax	0.539265	0.460735
Over20Y	Black High	Medium	Handysize	0.001003	0.998997
Over20Y	Black High	Medium	Panamax	0.545160	0.454840
Over20Y	Black High	Medium	Small	0.001150	0.998850
Over20Y	Black High	Very Low	Capesize	0.574570	0.425430
Over20Y	Black High	Very Low	Handymax	0.544393	0.455607
Over20Y	Black High	Very Low	Handysize	0.001322	0.998678
Over20Y	Black High	Very Low	Panamax	0.544796	0.455204
Over20Y	Black High	Very Low	Small	0.001096	0.998904
Over20Y	Black	High	Capesize	0.998802	0.001199
Over20Y	Black	High	Handymax	0.998958	0.001042
Over20Y	Black	High	Handysize	0.998632	0.001368
Over20Y	Black	High	Panamax	0.998739	0.001261
Over20Y	Black	High	Small	0.001264	0.998736

Over20Y	Black	Low	Capesize	0.541464	0.458536
Over20Y	Black	Low	Handymax	0.579570	0.420430
Over20Y	Black	Low	Handysize	0.001183	0.998817
Over20Y	Black	Low	Panamax	0.467310	0.532690
Over20Y	Black	Low	Small	0.001331	0.998669
Over20Y	Black	Medium	Capesize	0.519371	0.480629
Over20Y	Black	Medium	Handymax	0.519094	0.480906
Over20Y	Black	Medium	Handysize	0.001228	0.998772
Over20Y	Black	Medium	Panamax	0.532309	0.467691
Over20Y	Black	Medium	Small	0.001462	0.998538
Over20Y	Black	Very Low	Capesize	0.511952	0.488048
Over20Y	Black	Very Low	Handymax	0.500780	0.499220
Over20Y	Black	Very Low	Handysize	0.001644	0.998356
Over20Y	Black	Very Low	Panamax	0.457193	0.542807
Over20Y	Black	Very Low	Small	0.001554	0.998447
Over20Y	Grey	High	Capesize	0.449270	0.550730
Over20Y	Grey	High	Handymax	0.998573	0.001428
Over20Y	Grey	High	Handysize	0.998713	0.001287
Over20Y	Grey	High	Panamax	0.554821	0.445179
Over20Y	Grey	High	Small	0.998825	0.001175
Over20Y	Grey	Low	Capesize	0.482980	0.517020
Over20Y	Grey	Low	Handymax	0.523341	0.476660
Over20Y	Grey	Low	Handysize	0.000981	0.999019
Over20Y	Grey	Low	Panamax	0.552643	0.447357
Over20Y	Grey	Low	Small	0.001159	0.998841
Over20Y	Grey	Medium	Capesize	0.548354	0.451646
Over20Y	Grey	Medium	Handymax	0.474055	0.525945
Over20Y	Grey	Medium	Handysize	0.999057	0.000943
Over20Y	Grey	Medium	Panamax	0.508330	0.491670
Over20Y	Grey	Medium	Small	0.998793	0.001208

Over20Y	Grey	Very Low	Capesize	0.536479	0.463521
Over20Y	Grey	Very Low	Handymax	0.517227	0.482773
Over20Y	Grey	Very Low	Handysize	0.001359	0.998641
Over20Y	Grey	Very Low	Panamax	0.494512	0.505488
Over20Y	Grey	Very Low	Small	0.001677	0.998323
Over20Y	White	High	Capesize	0.998626	0.001374
Over20Y	White	High	Handymax	0.998769	0.001231
Over20Y	White	High	Handysize	0.998476	0.001524
Over20Y	White	High	Panamax	0.998447	0.001553
Over20Y	White	High	Small	0.998442	0.001558
Over20Y	White	Low	Capesize	0.495746	0.504254
Over20Y	White	Low	Handymax	0.464595	0.535405
Over20Y	White	Low	Handysize	0.496204	0.503796
Over20Y	White	Low	Panamax	0.486205	0.513795
Over20Y	White	Low	Small	0.001225	0.998775
Over20Y	White	Medium	Capesize	0.551792	0.448208
Over20Y	White	Medium	Handymax	0.539596	0.460404
Over20Y	White	Medium	Handysize	0.998808	0.001192
Over20Y	White	Medium	Panamax	0.528448	0.471552
Over20Y	White	Medium	Small	0.998402	0.001598
Over20Y	White	Very Low	Capesize	0.500091	0.499909
Over20Y	White	Very Low	Handymax	0.473962	0.526038
Over20Y	White	Very Low	Handysize	0.520756	0.479244
Over20Y	White	Very Low	Panamax	0.421148	0.578852
Over20Y	White	Very Low	Small	0.001258	0.998742
0to5Y	Black High	High	Capesize	0.566632	0.433368
0to5Y	Black High	High	Handymax	0.471802	0.528198
0to5Y	Black High	High	Handysize	0.495600	0.504400
0to5Y	Black High	High	Panamax	0.568231	0.431769
0to5Y	Black High	High	Small	0.439828	0.560172

0to5Y	Black High	Low	Capesize	0.539685	0.460315
0to5Y	Black High	Low	Handymax	0.521961	0.478039
0to5Y	Black High	Low	Handysize	0.520709	0.479291
0to5Y	Black High	Low	Panamax	0.449641	0.550359
0to5Y	Black High	Low	Small	0.522040	0.477960
0to5Y	Black High	Medium	Capesize	0.479162	0.520838
0to5Y	Black High	Medium	Handymax	0.483724	0.516276
0to5Y	Black High	Medium	Handysize	0.500785	0.499215
0to5Y	Black High	Medium	Panamax	0.491046	0.508955
0to5Y	Black High	Medium	Small	0.441957	0.558043
0to5Y	Black High	Very Low	Capesize	0.526667	0.473333
0to5Y	Black High	Very Low	Handymax	0.530375	0.469625
0to5Y	Black High	Very Low	Handysize	0.474196	0.525804
0to5Y	Black High	Very Low	Panamax	0.467143	0.532857
0to5Y	Black High	Very Low	Small	0.462267	0.537732
0to5Y	Black	High	Capesize	0.497098	0.502902
0to5Y	Black	High	Handymax	0.998795	0.001205
0to5Y	Black	High	Handysize	0.998749	0.001251
0to5Y	Black	High	Panamax	0.998657	0.001343
0to5Y	Black	High	Small	0.998996	0.001004
0to5Y	Black	Low	Capesize	0.493746	0.506254
0to5Y	Black	Low	Handymax	0.508484	0.491516
0to5Y	Black	Low	Handysize	0.555844	0.444156
0to5Y	Black	Low	Panamax	0.448002	0.551998
0to5Y	Black	Low	Small	0.560544	0.439456
0to5Y	Black	Medium	Capesize	0.509964	0.490036
0to5Y	Black	Medium	Handymax	0.493966	0.506033
0to5Y	Black	Medium	Handysize	0.484747	0.515253
0to5Y	Black	Medium	Panamax	0.555745	0.444255
0to5Y	Black	Medium	Small	0.503757	0.496243

0to5Y	Black	Very Low	Capesize	0.470815	0.529185
0to5Y	Black	Very Low	Handymax	0.423796	0.576204
0to5Y	Black	Very Low	Handysize	0.427791	0.572209
0to5Y	Black	Very Low	Panamax	0.511001	0.488999
0to5Y	Black	Very Low	Small	0.503970	0.496030
0to5Y	Grey	High	Capesize	0.508868	0.491132
0to5Y	Grey	High	Handymax	0.998761	0.001239
0to5Y	Grey	High	Handysize	0.998764	0.001236
0to5Y	Grey	High	Panamax	0.490966	0.509034
0to5Y	Grey	High	Small	0.998673	0.001327
0to5Y	Grey	Low	Capesize	0.541796	0.458204
0to5Y	Grey	Low	Handymax	0.488519	0.511482
0to5Y	Grey	Low	Handysize	0.453426	0.546574
0to5Y	Grey	Low	Panamax	0.516532	0.483468
0to5Y	Grey	Low	Small	0.512979	0.487021
0to5Y	Grey	Medium	Capesize	0.464614	0.535386
0to5Y	Grey	Medium	Handymax	0.482553	0.517447
0to5Y	Grey	Medium	Handysize	0.998691	0.001309
0to5Y	Grey	Medium	Panamax	0.493251	0.506749
0to5Y	Grey	Medium	Small	0.486461	0.513539
0to5Y	Grey	Very Low	Capesize	0.483776	0.516224
0to5Y	Grey	Very Low	Handymax	0.528588	0.471412
0to5Y	Grey	Very Low	Handysize	0.474382	0.525618
0to5Y	Grey	Very Low	Panamax	0.481727	0.518273
0to5Y	Grey	Very Low	Small	0.998562	0.001438
0to5Y	White	High	Capesize	0.998605	0.001395
0to5Y	White	High	Handymax	0.998705	0.001295
0to5Y	White	High	Handysize	0.999039	0.000961
0to5Y	White	High	Panamax	0.998843	0.001157
0to5Y	White	High	Small	0.998463	0.001537

0to5Y	White	Low	Capesize	0.452226	0.547773
0to5Y	White	Low	Handymax	0.498157	0.501843
0to5Y	White	Low	Handysize	0.428092	0.571908
0to5Y	White	Low	Panamax	0.512083	0.487917
0to5Y	White	Low	Small	0.472032	0.527968
0to5Y	White	Medium	Capesize	0.505572	0.494428
0to5Y	White	Medium	Handymax	0.515100	0.484900
0to5Y	White	Medium	Handysize	0.568382	0.431618
0to5Y	White	Medium	Panamax	0.504945	0.495055
0to5Y	White	Medium	Small	0.532736	0.467265
0to5Y	White	Very Low	Capesize	0.456676	0.543324
0to5Y	White	Very Low	Handymax	0.551240	0.448760
0to5Y	White	Very Low	Handysize	0.467653	0.532347
0to5Y	White	Very Low	Panamax	0.461626	0.538374
0to5Y	White	Very Low	Small	0.488329	0.511670
10to15Y	Black High	High	Capesize	0.498547	0.501453
10to15Y	Black High	High	Handymax	0.999041	0.000959
10to15Y	Black High	High	Handysize	0.531082	0.468918
10to15Y	Black High	High	Panamax	0.466351	0.533649
10to15Y	Black High	High	Small	0.486974	0.513026
10to15Y	Black High	Low	Capesize	0.538057	0.461943
10to15Y	Black High	Low	Handymax	0.513534	0.486466
10to15Y	Black High	Low	Handysize	0.521195	0.478805
10to15Y	Black High	Low	Panamax	0.472977	0.527023
10to15Y	Black High	Low	Small	0.512607	0.487393
10to15Y	Black High	Medium	Capesize	0.546693	0.453307
10to15Y	Black High	Medium	Handymax	0.472477	0.527523
10to15Y	Black High	Medium	Handysize	0.501000	0.499000
10to15Y	Black High	Medium	Panamax	0.531949	0.468051
10to15Y	Black High	Medium	Small	0.428476	0.571524

10to15Y	Black High	Very Low	Capesize	0.501797	0.498203
10to15Y	Black High	Very Low	Handymax	0.510860	0.489140
10to15Y	Black High	Very Low	Handysize	0.506152	0.493848
10to15Y	Black High	Very Low	Panamax	0.485230	0.514770
10to15Y	Black High	Very Low	Small	0.506461	0.493539
10to15Y	Black	High	Capesize	0.998576	0.001424
10to15Y	Black	High	Handymax	0.999114	0.000886
10to15Y	Black	High	Handysize	0.998704	0.001296
10to15Y	Black	High	Panamax	0.998943	0.001057
10to15Y	Black	High	Small	0.999005	0.000995
10to15Y	Black	Low	Capesize	0.525703	0.474297
10to15Y	Black	Low	Handymax	0.542037	0.457963
10to15Y	Black	Low	Handysize	0.544487	0.455512
10to15Y	Black	Low	Panamax	0.554161	0.445839
10to15Y	Black	Low	Small	0.510337	0.489663
10to15Y	Black	Medium	Capesize	0.483290	0.516710
10to15Y	Black	Medium	Handymax	0.560303	0.439697
10to15Y	Black	Medium	Handysize	0.497507	0.502493
10to15Y	Black	Medium	Panamax	0.520582	0.479418
10to15Y	Black	Medium	Small	0.545295	0.454705
10to15Y	Black	Very Low	Capesize	0.532768	0.467232
10to15Y	Black	Very Low	Handymax	0.544874	0.455126
10to15Y	Black	Very Low	Handysize	0.505890	0.494110
10to15Y	Black	Very Low	Panamax	0.569973	0.430027
10to15Y	Black	Very Low	Small	0.491321	0.508679
10to15Y	Grey	High	Capesize	0.543605	0.456395
10to15Y	Grey	High	Handymax	0.998876	0.001124
10to15Y	Grey	High	Handysize	0.998497	0.001503
10to15Y	Grey	High	Panamax	0.998897	0.001103
10to15Y	Grey	High	Small	0.998828	0.001171

10to15Y	Grey	Low	Capesize	0.438238	0.561762
10to15Y	Grey	Low	Handymax	0.515554	0.484446
10to15Y	Grey	Low	Handysize	0.506032	0.493968
10to15Y	Grey	Low	Panamax	0.467327	0.532673
10to15Y	Grey	Low	Small	0.452261	0.547739
10to15Y	Grey	Medium	Capesize	0.533832	0.466168
10to15Y	Grey	Medium	Handymax	0.998630	0.001370
10to15Y	Grey	Medium	Handysize	0.998891	0.001109
10to15Y	Grey	Medium	Panamax	0.483286	0.516714
10to15Y	Grey	Medium	Small	0.516806	0.483194
10to15Y	Grey	Very Low	Capesize	0.511030	0.488970
10to15Y	Grey	Very Low	Handymax	0.491322	0.508678
10to15Y	Grey	Very Low	Handysize	0.509913	0.490087
10to15Y	Grey	Very Low	Panamax	0.546176	0.453824
10to15Y	Grey	Very Low	Small	0.499749	0.500251
10to15Y	White	High	Capesize	0.998764	0.001236
10to15Y	White	High	Handymax	0.998480	0.001520
10to15Y	White	High	Handysize	0.998856	0.001144
10to15Y	White	High	Panamax	0.998962	0.001038
10to15Y	White	High	Small	0.998622	0.001378
10to15Y	White	Low	Capesize	0.546209	0.453791
10to15Y	White	Low	Handymax	0.560882	0.439118
10to15Y	White	Low	Handysize	0.001247	0.998753
10to15Y	White	Low	Panamax	0.530591	0.469409
10to15Y	White	Low	Small	0.529009	0.470991
10to15Y	White	Medium	Capesize	0.581359	0.418641
10to15Y	White	Medium	Handymax	0.568720	0.431280
10to15Y	White	Medium	Handysize	0.998775	0.001225
10to15Y	White	Medium	Panamax	0.497082	0.502918
10to15Y	White	Medium	Small	0.517365	0.482635

10to15Y	White	Very Low	Capesize	0.497770	0.502230
10to15Y	White	Very Low	Handymax	0.472753	0.527247
10to15Y	White	Very Low	Handysize	0.565863	0.434137
10to15Y	White	Very Low	Panamax	0.439963	0.560037
10to15Y	White	Very Low	Small	0.522295	0.477705
15to20Y	Black High	High	Capesize	0.514493	0.485507
15to20Y	Black High	High	Handymax	0.462981	0.537019
15to20Y	Black High	High	Handysize	0.566093	0.433907
15to20Y	Black High	High	Panamax	0.528398	0.471602
15to20Y	Black High	High	Small	0.503993	0.496007
15to20Y	Black High	Low	Capesize	0.575465	0.424535
15to20Y	Black High	Low	Handymax	0.488846	0.511154
15to20Y	Black High	Low	Handysize	0.482407	0.517593
15to20Y	Black High	Low	Panamax	0.497981	0.502019
15to20Y	Black High	Low	Small	0.521280	0.478720
15to20Y	Black High	Medium	Capesize	0.454674	0.545326
15to20Y	Black High	Medium	Handymax	0.582944	0.417056
15to20Y	Black High	Medium	Handysize	0.454308	0.545692
15to20Y	Black High	Medium	Panamax	0.475279	0.524721
15to20Y	Black High	Medium	Small	0.494224	0.505776
15to20Y	Black High	Very Low	Capesize	0.492945	0.507056
15to20Y	Black High	Very Low	Handymax	0.576767	0.423233
15to20Y	Black High	Very Low	Handysize	0.522366	0.477634
15to20Y	Black High	Very Low	Panamax	0.511211	0.488789
15to20Y	Black High	Very Low	Small	0.569226	0.430774
15to20Y	Black	High	Capesize	0.517820	0.482180
15to20Y	Black	High	Handymax	0.998639	0.001361
15to20Y	Black	High	Handysize	0.998867	0.001133
15to20Y	Black	High	Panamax	0.998660	0.001340
15to20Y	Black	High	Small	0.999086	0.000914

15to20Y	Black	Low	Capesize	0.504463	0.495537
15to20Y	Black	Low	Handymax	0.505465	0.494535
15to20Y	Black	Low	Handysize	0.477150	0.522850
15to20Y	Black	Low	Panamax	0.491531	0.508469
15to20Y	Black	Low	Small	0.514412	0.485588
15to20Y	Black	Medium	Capesize	0.455049	0.544951
15to20Y	Black	Medium	Handymax	0.440783	0.559217
15to20Y	Black	Medium	Handysize	0.998895	0.001105
15to20Y	Black	Medium	Panamax	0.467009	0.532991
15to20Y	Black	Medium	Small	0.001323	0.998677
15to20Y	Black	Very Low	Capesize	0.439175	0.560825
15to20Y	Black	Very Low	Handymax	0.443549	0.556452
15to20Y	Black	Very Low	Handysize	0.523307	0.476693
15to20Y	Black	Very Low	Panamax	0.472542	0.527458
15to20Y	Black	Very Low	Small	0.503639	0.496361
15to20Y	Grey	High	Capesize	0.475912	0.524088
15to20Y	Grey	High	Handymax	0.998778	0.001222
15to20Y	Grey	High	Handysize	0.998991	0.001009
15to20Y	Grey	High	Panamax	0.998612	0.001388
15to20Y	Grey	High	Small	0.001276	0.998724
15to20Y	Grey	Low	Capesize	0.472986	0.527014
15to20Y	Grey	Low	Handymax	0.525542	0.474458
15to20Y	Grey	Low	Handysize	0.535102	0.464898
15to20Y	Grey	Low	Panamax	0.559704	0.440296
15to20Y	Grey	Low	Small	0.525466	0.474534
15to20Y	Grey	Medium	Capesize	0.469900	0.530100
15to20Y	Grey	Medium	Handymax	0.998980	0.001020
15to20Y	Grey	Medium	Handysize	0.504219	0.495780
15to20Y	Grey	Medium	Panamax	0.484983	0.515017
15to20Y	Grey	Medium	Small	0.494845	0.505155

15to20Y	Grey	Very Low	Capesize	0.535978	0.464022
15to20Y	Grey	Very Low	Handymax	0.449547	0.550453
15to20Y	Grey	Very Low	Handysize	0.498878	0.501122
15to20Y	Grey	Very Low	Panamax	0.552445	0.447555
15to20Y	Grey	Very Low	Small	0.487671	0.512330
15to20Y	White	High	Capesize	0.998669	0.001331
15to20Y	White	High	Handymax	0.998944	0.001056
15to20Y	White	High	Handysize	0.998735	0.001265
15to20Y	White	High	Panamax	0.998757	0.001243
15to20Y	White	High	Small	0.999013	0.000987
15to20Y	White	Low	Capesize	0.482941	0.517059
15to20Y	White	Low	Handymax	0.511710	0.488290
15to20Y	White	Low	Handysize	0.462059	0.537941
15to20Y	White	Low	Panamax	0.560295	0.439705
15to20Y	White	Low	Small	0.547264	0.452736
15to20Y	White	Medium	Capesize	0.505111	0.494889
15to20Y	White	Medium	Handymax	0.556827	0.443173
15to20Y	White	Medium	Handysize	0.511153	0.488847
15to20Y	White	Medium	Panamax	0.483683	0.516317
15to20Y	White	Medium	Small	0.460821	0.539179
15to20Y	White	Very Low	Capesize	0.485914	0.514086
15to20Y	White	Very Low	Handymax	0.456901	0.543099
15to20Y	White	Very Low	Handysize	0.430519	0.569480
15to20Y	White	Very Low	Panamax	0.490706	0.509294
15to20Y	White	Very Low	Small	0.454168	0.545832
5to10Y	Black High	High	Capesize	0.563230	0.436770
5to10Y	Black High	High	Handymax	0.505653	0.494347
5to10Y	Black High	High	Handysize	0.440018	0.559982
5to10Y	Black High	High	Panamax	0.503455	0.496545
5to10Y	Black High	High	Small	0.492448	0.507552

5to10Y	Black High	Low	Capesize	0.494184	0.505816
5to10Y	Black High	Low	Handymax	0.472352	0.527648
5to10Y	Black High	Low	Handysize	0.527356	0.472644
5to10Y	Black High	Low	Panamax	0.458931	0.541069
5to10Y	Black High	Low	Small	0.451886	0.548114
5to10Y	Black High	Medium	Capesize	0.520759	0.479241
5to10Y	Black High	Medium	Handymax	0.436984	0.563016
5to10Y	Black High	Medium	Handysize	0.448729	0.551271
5to10Y	Black High	Medium	Panamax	0.474434	0.525566
5to10Y	Black High	Medium	Small	0.516272	0.483728
5to10Y	Black High	Very Low	Capesize	0.486962	0.513038
5to10Y	Black High	Very Low	Handymax	0.580543	0.419457
5to10Y	Black High	Very Low	Handysize	0.528309	0.471691
5to10Y	Black High	Very Low	Panamax	0.478332	0.521668
5to10Y	Black High	Very Low	Small	0.541163	0.458837
5to10Y	Black	High	Capesize	0.998546	0.001454
5to10Y	Black	High	Handymax	0.999013	0.000987
5to10Y	Black	High	Handysize	0.998856	0.001144
5to10Y	Black	High	Panamax	0.525954	0.474046
5to10Y	Black	High	Small	0.998838	0.001162
5to10Y	Black	Low	Capesize	0.470390	0.529610
5to10Y	Black	Low	Handymax	0.496039	0.503961
5to10Y	Black	Low	Handysize	0.546972	0.453028
5to10Y	Black	Low	Panamax	0.473791	0.526209
5to10Y	Black	Low	Small	0.511218	0.488782
5to10Y	Black	Medium	Capesize	0.568984	0.431016
5to10Y	Black	Medium	Handymax	0.427974	0.572026
5to10Y	Black	Medium	Handysize	0.461970	0.538030
5to10Y	Black	Medium	Panamax	0.497268	0.502732
5to10Y	Black	Medium	Small	0.501734	0.498266

5to10Y	Black	Very Low	Capesize	0.528275	0.471725
5to10Y	Black	Very Low	Handymax	0.502837	0.497163
5to10Y	Black	Very Low	Handysize	0.544233	0.455767
5to10Y	Black	Very Low	Panamax	0.455283	0.544717
5to10Y	Black	Very Low	Small	0.480791	0.519209
5to10Y	Grey	High	Capesize	0.492491	0.507510
5to10Y	Grey	High	Handymax	0.999020	0.000980
5to10Y	Grey	High	Handysize	0.998717	0.001283
5to10Y	Grey	High	Panamax	0.460686	0.539314
5to10Y	Grey	High	Small	0.998769	0.001232
5to10Y	Grey	Low	Capesize	0.476762	0.523238
5to10Y	Grey	Low	Handymax	0.561636	0.438363
5to10Y	Grey	Low	Handysize	0.505199	0.494801
5to10Y	Grey	Low	Panamax	0.440672	0.559328
5to10Y	Grey	Low	Small	0.485221	0.514779
5to10Y	Grey	Medium	Capesize	0.484090	0.515910
5to10Y	Grey	Medium	Handymax	0.998644	0.001355
5to10Y	Grey	Medium	Handysize	0.999093	0.000907
5to10Y	Grey	Medium	Panamax	0.558847	0.441153
5to10Y	Grey	Medium	Small	0.998731	0.001269
5to10Y	Grey	Very Low	Capesize	0.545163	0.454837
5to10Y	Grey	Very Low	Handymax	0.518013	0.481987
5to10Y	Grey	Very Low	Handysize	0.497028	0.502972
5to10Y	Grey	Very Low	Panamax	0.557708	0.442292
5to10Y	Grey	Very Low	Small	0.998792	0.001208
5to10Y	White	High	Capesize	0.998652	0.001348
5to10Y	White	High	Handymax	0.998643	0.001357
5to10Y	White	High	Handysize	0.998739	0.001261
5to10Y	White	High	Panamax	0.431190	0.568810
5to10Y	White	High	Small	0.998809	0.001191

5to10Y	White	Low	Capesize	0.484700	0.515300
5to10Y	White	Low	Handymax	0.536964	0.463036
5to10Y	White	Low	Handysize	0.998792	0.001208
5to10Y	White	Low	Panamax	0.499555	0.500445
5to10Y	White	Low	Small	0.453327	0.546673
5to10Y	White	Medium	Capesize	0.571370	0.428630
5to10Y	White	Medium	Handymax	0.478630	0.521370
5to10Y	White	Medium	Handysize	0.420012	0.579988
5to10Y	White	Medium	Panamax	0.523754	0.476246
5to10Y	White	Medium	Small	0.998459	0.001541
5to10Y	White	Very Low	Capesize	0.550783	0.449217
5to10Y	White	Very Low	Handymax	0.449154	0.550846
5to10Y	White	Very Low	Handysize	0.469060	0.530940
5to10Y	White	Very Low	Panamax	0.470361	0.529639
5to10Y	White	Very Low	Small	0.511081	0.488919

Table Appendix 1.2. CPT of ‘Inspection group’

Port of inspection	Type of inspection	Number of deficiencies	Low Detention Risk	High Detention Risk
Belgium	Expanded Inspection	4to9	0.998672	0.001328
Belgium	Expanded Inspection	More than 10	0.001474	0.998526
Belgium	Expanded Inspection	0	0.998588	0.001412
Belgium	Expanded Inspection	1to3	0.998693	0.001307
Belgium	Initial Inspection	4to9	0.998886	0.001114
Belgium	Initial Inspection	More than 10	0.508011	0.491989
Belgium	Initial Inspection	0	0.998982	0.001018
Belgium	Initial Inspection	1to3	0.998892	0.001108
Belgium	More detailed Inspection	4to9	0.998702	0.001298
Belgium	More detailed Inspection	More than 10	0.001630	0.998370
Belgium	More detailed Inspection	0	0.998878	0.001122
Belgium	More detailed Inspection	1to3	0.998792	0.001208

France	Expanded Inspection	4to9	0.999023	0.000977
France	Expanded Inspection	More than 10	0.001228	0.998772
France	Expanded Inspection	0	0.999027	0.000973
France	Expanded Inspection	1to3	0.999051	0.000949
France	Initial Inspection	4to9	0.998572	0.001428
France	Initial Inspection	More than 10	0.998878	0.001122
France	Initial Inspection	0	0.998584	0.001416
France	Initial Inspection	1to3	0.999035	0.000965
France	More detailed Inspection	4to9	0.998629	0.001371
France	More detailed Inspection	More than 10	0.001292	0.998708
France	More detailed Inspection	0	0.998896	0.001104
France	More detailed Inspection	1to3	0.998563	0.001437
Germany	Expanded Inspection	4to9	0.998665	0.001335
Germany	Expanded Inspection	More than 10	0.001290	0.998710
Germany	Expanded Inspection	0	0.998803	0.001197
Germany	Expanded Inspection	1to3	0.998840	0.001160
Germany	Initial Inspection	4to9	0.998675	0.001325
Germany	Initial Inspection	More than 10	0.565841	0.434159
Germany	Initial Inspection	0	0.998481	0.001519
Germany	Initial Inspection	1to3	0.998880	0.001120
Germany	More detailed Inspection	4to9	0.998734	0.001266
Germany	More detailed Inspection	More than 10	0.001332	0.998668
Germany	More detailed Inspection	0	0.998962	0.001038
Germany	More detailed Inspection	1to3	0.998836	0.001164
Italy	Expanded Inspection	4to9	0.998855	0.001145
Italy	Expanded Inspection	More than 10	0.001201	0.998799
Italy	Expanded Inspection	0	0.998706	0.001294
Italy	Expanded Inspection	1to3	0.998868	0.001132
Italy	Initial Inspection	4to9	0.998760	0.001240
Italy	Initial Inspection	More than 10	0.514740	0.485260

Italy	Initial Inspection	0	0.998763	0.001237
Italy	Initial Inspection	1to3	0.998552	0.001448
Italy	More detailed Inspection	4to9	0.998876	0.001124
Italy	More detailed Inspection	More than 10	0.000955	0.999045
Italy	More detailed Inspection	0	0.998663	0.001337
Italy	More detailed Inspection	1to3	0.999127	0.000873
Netherlands	Expanded Inspection	4to9	0.998806	0.001194
Netherlands	Expanded Inspection	More than 10	0.001520	0.998480
Netherlands	Expanded Inspection	0	0.998828	0.001172
Netherlands	Expanded Inspection	1to3	0.998811	0.001189
Netherlands	Initial Inspection	4to9	0.998627	0.001373
Netherlands	Initial Inspection	More than 10	0.511498	0.488502
Netherlands	Initial Inspection	0	0.998754	0.001246
Netherlands	Initial Inspection	1to3	0.998768	0.001232
Netherlands	More detailed Inspection	4to9	0.998799	0.001201
Netherlands	More detailed Inspection	More than 10	0.001244	0.998756
Netherlands	More detailed Inspection	0	0.998664	0.001336
Netherlands	More detailed Inspection	1to3	0.998896	0.001104
Spain	Expanded Inspection	4to9	0.998686	0.001314
Spain	Expanded Inspection	More than 10	0.001059	0.998941
Spain	Expanded Inspection	0	0.998519	0.001481
Spain	Expanded Inspection	1to3	0.998380	0.001620
Spain	Initial Inspection	4to9	0.998973	0.001027
Spain	Initial Inspection	More than 10	0.998712	0.001288
Spain	Initial Inspection	0	0.998492	0.001508
Spain	Initial Inspection	1to3	0.999004	0.000996
Spain	More detailed Inspection	4to9	0.998865	0.001135
Spain	More detailed Inspection	More than 10	0.001362	0.998638
Spain	More detailed Inspection	0	0.998654	0.001346
Spain	More detailed Inspection	1to3	0.998589	0.001411

UK	Expanded Inspection	4to9	0.998635	0.001365
UK	Expanded Inspection	More than 10	0.001125	0.998875
UK	Expanded Inspection	0	0.998738	0.001262
UK	Expanded Inspection	1to3	0.998528	0.001472
UK	Initial Inspection	4to9	0.998838	0.001162
UK	Initial Inspection	More than 10	0.001164	0.998836
UK	Initial Inspection	0	0.998960	0.001040
UK	Initial Inspection	1to3	0.998645	0.001355
UK	More detailed Inspection	4to9	0.998618	0.001382
UK	More detailed Inspection	More than 10	0.001296	0.998704
UK	More detailed Inspection	0	0.998956	0.001044
UK	More detailed Inspection	1to3	0.998536	0.001464

Appendix Two Conditional Probability table of 'Post-NIR' BN model

Table Appendix 2.1. CPT of 'Vessel flag'

White	Grey	Black	Black High
0.966385	0.015013	0.010865	0.007737

Table Appendix 2.2. CPT of 'Vessel age'

0to5Y	5to10Y	10to15Y	15to20Y	Over20Y
0.263269	0.388449	0.187637	0.105098	0.055547

Table Appendix 2.3. CPT of 'Inspection date'

Y2015	Y2016	Y2017
0.298343	0.408941	0.292717

Table Appendix 2.4. CPT of 'Port of inspection'

Belgium	Canada	France	Germany	Greece	Italy	Netherlands	Spain	UK
0.060129	0.165029	0.078810	0.076657	0.088918	0.118866	0.147362	0.154592	0.109636

Table Appendix 2.5. CPT of 'Inspection type'

Initial Inspection	Expanded Inspection	More detailed Inspection
0.344691	0.223446	0.431863

Table Appendix 2.6. CPT of ‘Company performance’

Vessel flag	**Vessel age**	**High**	**Medium**	**Low**	**Very low**
White	0to5Y	0.103702	0.784361	0.094985	0.016952
White	5to10Y	0.066715	0.803925	0.093230	0.036130
White	10to15Y	0.068996	0.664588	0.186930	0.079486
White	15to20Y	0.067643	0.558777	0.260890	0.112690
White	Over20Y	0.032213	0.502782	0.213373	0.251632
Grey	0to5Y	0.023868	0.958627	0.008714	0.008791
Grey	5to10Y	0.030190	0.884997	0.030198	0.054615
Grey	10to15Y	0.158135	0.481331	0.158143	0.202390
Grey	15to20Y	0.009966	0.638256	0.192568	0.159209
Grey	Over20Y	0.009629	0.665282	0.051950	0.273140
Black	0to5Y	0.008606	0.973096	0.009149	0.009149
Black	5to10Y	0.010770	0.967459	0.010963	0.010808
Black	10to15Y	0.012665	0.216921	0.106974	0.663440
Black	15to20Y	0.012667	0.296666	0.096159	0.594508
Black	Over20Y	0.070320	0.373660	0.212134	0.343886
Black (High)	0to5Y	0.222641	0.291587	0.243652	0.242120
Black (High)	5to10Y	0.236069	0.238210	0.254883	0.270839
Black (High)	10to15Y	0.245896	0.247057	0.268285	0.238762
Black (High)	15to20Y	0.010848	0.010934	0.489779	0.488439
Black (High)	Over20Y	0.010541	0.010705	0.656032	0.322722

Table Appendix 2.7. CPT of ‘Number of deficiencies’

Inspection type	Vessel group	None	1to3	4to9	Morethan10
Initial Inspection	High Detention Risk	0.515492	0.386232	0.083816	0.014460
Initial Inspection	Low Detention Risk	0.667770	0.282785	0.039361	0.010084
Expanded Inspection	High Detention Risk	0.100674	0.287451	0.328104	0.283771
Expanded Inspection	Low Detention Risk	0.292678	0.401085	0.255760	0.050477
More detailed Inspection	High Detention Risk	0.186452	0.349807	0.263075	0.200666
More detailed Inspection	Low Detention Risk	0.485976	0.300957	0.186952	0.026114

Table Appendix 2.8. CPT of ‘Vessel group’

Vessel flag	Vessel age	Company performance	High Detention Risk	Low Detention Risk
White	0to5Y	High	0.004537	0.995463
White	0to5Y	Medium	0.003798	0.996202
White	0to5Y	Low	0.003864	0.996136
White	0to5Y	Very low	0.995783	0.004217
White	5to10Y	High	0.003800	0.996200
White	5to10Y	Medium	0.003854	0.996146
White	5to10Y	Low	0.995554	0.004446
White	5to10Y	Very low	0.997017	0.002983
White	10to15Y	High	0.004118	0.995882
White	10to15Y	Medium	0.003207	0.996793
White	10to15Y	Low	0.002873	0.997127
White	10to15Y	Very low	0.995912	0.004088
White	15to20Y	High	0.003671	0.996329
White	15to20Y	Medium	0.003101	0.996899
White	15to20Y	Low	0.997281	0.002719
White	15to20Y	Very low	0.996162	0.003838
White	Over20Y	High	0.003510	0.996490
White	Over20Y	Medium	0.003958	0.996042
White	Over20Y	Low	0.995615	0.004385

White	Over20Y	Very low	0.995895	0.004105
Grey	0to5Y	High	0.002980	0.997020
Grey	0to5Y	Medium	0.003945	0.996055
Grey	0to5Y	Low	0.512477	0.487523
Grey	0to5Y	Very low	0.500577	0.499423
Grey	5to10Y	High	0.002929	0.997071
Grey	5to10Y	Medium	0.003520	0.996480
Grey	5to10Y	Low	0.004595	0.995405
Grey	5to10Y	Very low	0.003786	0.996214
Grey	10to15Y	High	0.003465	0.996535
Grey	10to15Y	Medium	0.002854	0.997146
Grey	10to15Y	Low	0.003975	0.996025
Grey	10to15Y	Very low	0.995828	0.004172
Grey	15to20Y	High	0.523022	0.476978
Grey	15to20Y	Medium	0.004802	0.995198
Grey	15to20Y	Low	0.003686	0.996315
Grey	15to20Y	Very low	0.003316	0.996684
Grey	Over20Y	High	0.568076	0.431924
Grey	Over20Y	Medium	0.003902	0.996098
Grey	Over20Y	Low	0.996155	0.003845
Grey	Over20Y	Very low	0.996345	0.003655
Black	0to5Y	High	0.530280	0.469720
Black	0to5Y	Medium	0.004126	0.995874
Black	0to5Y	Low	0.466315	0.533685
Black	0to5Y	Very low	0.477942	0.522058
Black	5to10Y	High	0.536626	0.463374
Black	5to10Y	Medium	0.003894	0.996106
Black	5to10Y	Low	0.543236	0.456764
Black	5to10Y	Very low	0.536676	0.463324
Black	10to15Y	High	0.476661	0.523339

Black	10to15Y	Medium	0.004508	0.995492
Black	10to15Y	Low	0.004687	0.995313
Black	10to15Y	Very low	0.004645	0.995355
Black	15to20Y	High	0.452878	0.547122
Black	15to20Y	Medium	0.003347	0.996653
Black	15to20Y	Low	0.004677	0.995323
Black	15to20Y	Very low	0.996187	0.003813
Black	Over20Y	High	0.003228	0.996772
Black	Over20Y	Medium	0.004600	0.995400
Black	Over20Y	Low	0.995975	0.004025
Black	Over20Y	Very low	0.996992	0.003008
Black (High)	0to5Y	High	0.537779	0.462221
Black (High)	0to5Y	Medium	0.467681	0.532319
Black (High)	0to5Y	Low	0.492068	0.507932
Black (High)	0to5Y	Very low	0.535406	0.464595
Black (High)	5to10Y	High	0.562635	0.437364
Black (High)	5to10Y	Medium	0.543569	0.456431
Black (High)	5to10Y	Low	0.495379	0.504621
Black (High)	5to10Y	Very low	0.439403	0.560597
Black (High)	10to15Y	High	0.526571	0.473429
Black (High)	10to15Y	Medium	0.470854	0.529146
Black (High)	10to15Y	Low	0.504326	0.495674
Black (High)	10to15Y	Very low	0.521695	0.478305
Black (High)	15to20Y	High	0.478636	0.521364
Black (High)	15to20Y	Medium	0.447775	0.552225
Black (High)	15to20Y	Low	0.004422	0.995578
Black (High)	15to20Y	Very low	0.004809	0.995191
Black (High)	Over20Y	High	0.568038	0.431962
Black (High)	Over20Y	Medium	0.430261	0.569739
Black (High)	Over20Y	Low	0.996922	0.003078

Black (High)	Over20Y	Very low	0.997018	0.002983

Table Appendix 2.9. CPT of 'Inspection group'

Inspection port	Date	No. of deficiencies	Inspection type	High Risk	Low Risk
Belgium	Y2015	None	Initial inspection	0.003112	0.996889
Belgium	Y2015	None	Expanded inspection	0.003529	0.996471
Belgium	Y2015	None	More detailed inspection	0.003545	0.996455
Belgium	Y2015	1to3	Initial inspection	0.004226	0.995774
Belgium	Y2015	1to3	Expanded inspection	0.003712	0.996288
Belgium	Y2015	1to3	More detailed inspection	0.003831	0.996169
Belgium	Y2015	4to9	Initial inspection	0.004555	0.995445
Belgium	Y2015	4to9	Expanded inspection	0.004455	0.995545
Belgium	Y2015	4to9	More detailed inspection	0.003935	0.996065
Belgium	Y2015	Morethan10	Initial inspection	0.003987	0.996013
Belgium	Y2015	Morethan10	Expanded inspection	0.996410	0.003590
Belgium	Y2015	Morethan10	More detailed inspection	0.995239	0.004761
Belgium	Y2016	None	Initial inspection	0.003619	0.996381
Belgium	Y2016	None	Expanded inspection	0.537436	0.462564
Belgium	Y2016	None	More detailed inspection	0.003569	0.996431
Belgium	Y2016	1to3	Initial inspection	0.003277	0.996723
Belgium	Y2016	1to3	Expanded inspection	0.002981	0.997019
Belgium	Y2016	1to3	More detailed inspection	0.004125	0.995875
Belgium	Y2016	4to9	Initial inspection	0.004153	0.995847
Belgium	Y2016	4to9	Expanded inspection	0.003210	0.996790
Belgium	Y2016	4to9	More detailed inspection	0.003872	0.996128
Belgium	Y2016	Morethan10	Initial inspection	0.445086	0.554914
Belgium	Y2016	Morethan10	Expanded inspection	0.996818	0.003183
Belgium	Y2016	Morethan10	More detailed inspection	0.995947	0.004054
Belgium	Y2017	None	Initial inspection	0.004233	0.995767
Belgium	Y2017	None	Expanded inspection	0.003668	0.996332

Belgium	Y2017	None	More detailed inspection	0.003986	0.996014
Belgium	Y2017	1to3	Initial inspection	0.004758	0.995242
Belgium	Y2017	1to3	Expanded inspection	0.004749	0.995251
Belgium	Y2017	1to3	More detailed inspection	0.004473	0.995527
Belgium	Y2017	4to9	Initial inspection	0.002894	0.997106
Belgium	Y2017	4to9	Expanded inspection	0.003572	0.996428
Belgium	Y2017	4to9	More detailed inspection	0.004771	0.995229
Belgium	Y2017	Morethan10	Initial inspection	0.440615	0.559385
Belgium	Y2017	Morethan10	Expanded inspection	0.996363	0.003637
Belgium	Y2017	Morethan10	More detailed inspection	0.995390	0.004610
Canada	Y2015	None	Initial inspection	0.003824	0.996176
Canada	Y2015	None	Expanded inspection	0.004661	0.995339
Canada	Y2015	None	More detailed inspection	0.003514	0.996486
Canada	Y2015	1to3	Initial inspection	0.004399	0.995601
Canada	Y2015	1to3	Expanded inspection	0.003777	0.996223
Canada	Y2015	1to3	More detailed inspection	0.004762	0.995238
Canada	Y2015	4to9	Initial inspection	0.003139	0.996861
Canada	Y2015	4to9	Expanded inspection	0.003854	0.996145
Canada	Y2015	4to9	More detailed inspection	0.003110	0.996890
Canada	Y2015	Morethan10	Initial inspection	0.507885	0.492115
Canada	Y2015	Morethan10	Expanded inspection	0.995626	0.004374
Canada	Y2015	Morethan10	More detailed inspection	0.996840	0.003161
Canada	Y2016	None	Initial inspection	0.003803	0.996197
Canada	Y2016	None	Expanded inspection	0.003431	0.996569
Canada	Y2016	None	More detailed inspection	0.004342	0.995658
Canada	Y2016	1to3	Initial inspection	0.003657	0.996343
Canada	Y2016	1to3	Expanded inspection	0.003227	0.996773
Canada	Y2016	1to3	More detailed inspection	0.003711	0.996289
Canada	Y2016	4to9	Initial inspection	0.003180	0.996820
Canada	Y2016	4to9	Expanded inspection	0.003163	0.996836

Canada	Y2016	4to9	More detailed inspection	0.004109	0.995892
Canada	Y2016	Morethan10	Initial inspection	0.513746	0.486254
Canada	Y2016	Morethan10	Expanded inspection	0.996225	0.003775
Canada	Y2016	Morethan10	More detailed inspection	0.996366	0.003634
Canada	Y2017	None	Initial inspection	0.004455	0.995545
Canada	Y2017	None	Expanded inspection	0.005165	0.994835
Canada	Y2017	None	More detailed inspection	0.004651	0.995349
Canada	Y2017	1to3	Initial inspection	0.004850	0.995150
Canada	Y2017	1to3	Expanded inspection	0.003360	0.996640
Canada	Y2017	1to3	More detailed inspection	0.003589	0.996411
Canada	Y2017	4to9	Initial inspection	0.004132	0.995868
Canada	Y2017	4to9	Expanded inspection	0.003907	0.996093
Canada	Y2017	4to9	More detailed inspection	0.003274	0.996727
Canada	Y2017	Morethan10	Initial inspection	0.445746	0.554254
Canada	Y2017	Morethan10	Expanded inspection	0.996828	0.003172
Canada	Y2017	Morethan10	More detailed inspection	0.995762	0.004238
France	Y2015	None	Initial inspection	0.004048	0.995952
France	Y2015	None	Expanded inspection	0.003568	0.996432
France	Y2015	None	More detailed inspection	0.004357	0.995643
France	Y2015	1to3	Initial inspection	0.003242	0.996758
France	Y2015	1to3	Expanded inspection	0.004127	0.995873
France	Y2015	1to3	More detailed inspection	0.003087	0.996913
France	Y2015	4to9	Initial inspection	0.004376	0.995624
France	Y2015	4to9	Expanded inspection	0.003241	0.996759
France	Y2015	4to9	More detailed inspection	0.002795	0.997205
France	Y2015	Morethan10	Initial inspection	0.558207	0.441793
France	Y2015	Morethan10	Expanded inspection	0.996800	0.003200
France	Y2015	Morethan10	More detailed inspection	0.995654	0.004346
France	Y2016	None	Initial inspection	0.002913	0.997087
France	Y2016	None	Expanded inspection	0.003117	0.996883

France	Y2016	None	More detailed inspection	0.004079	0.995921
France	Y2016	1to3	Initial inspection	0.002993	0.997007
France	Y2016	1to3	Expanded inspection	0.002895	0.997105
France	Y2016	1to3	More detailed inspection	0.003730	0.996270
France	Y2016	4to9	Initial inspection	0.003998	0.996002
France	Y2016	4to9	Expanded inspection	0.004945	0.995055
France	Y2016	4to9	More detailed inspection	0.003875	0.996125
France	Y2016	Morethan10	Initial inspection	0.460867	0.539133
France	Y2016	Morethan10	Expanded inspection	0.996052	0.003948
France	Y2016	Morethan10	More detailed inspection	0.995445	0.004555
France	Y2017	None	Initial inspection	0.004500	0.995500
France	Y2017	None	Expanded inspection	0.003801	0.996199
France	Y2017	None	More detailed inspection	0.005311	0.994689
France	Y2017	1to3	Initial inspection	0.004438	0.995562
France	Y2017	1to3	Expanded inspection	0.003922	0.996078
France	Y2017	1to3	More detailed inspection	0.004918	0.995082
France	Y2017	4to9	Initial inspection	0.444324	0.555676
France	Y2017	4to9	Expanded inspection	0.004218	0.995782
France	Y2017	4to9	More detailed inspection	0.004560	0.995440
France	Y2017	Morethan10	Initial inspection	0.495239	0.504762
France	Y2017	Morethan10	Expanded inspection	0.996885	0.003114
France	Y2017	Morethan10	More detailed inspection	0.996153	0.003847
Germany	Y2015	None	Initial inspection	0.004030	0.995970
Germany	Y2015	None	Expanded inspection	0.003720	0.996280
Germany	Y2015	None	More detailed inspection	0.003878	0.996122
Germany	Y2015	1to3	Initial inspection	0.004235	0.995765
Germany	Y2015	1to3	Expanded inspection	0.003217	0.996783
Germany	Y2015	1to3	More detailed inspection	0.003421	0.996579
Germany	Y2015	4to9	Initial inspection	0.003402	0.996598
Germany	Y2015	4to9	Expanded inspection	0.995625	0.004375

Germany	Y2015	4to9	More detailed inspection	0.003404	0.996596
Germany	Y2015	Morethan10	Initial inspection	0.453446	0.546554
Germany	Y2015	Morethan10	Expanded inspection	0.995929	0.004071
Germany	Y2015	Morethan10	More detailed inspection	0.995503	0.004496
Germany	Y2016	None	Initial inspection	0.004115	0.995885
Germany	Y2016	None	Expanded inspection	0.003026	0.996974
Germany	Y2016	None	More detailed inspection	0.003939	0.996061
Germany	Y2016	1to3	Initial inspection	0.004582	0.995418
Germany	Y2016	1to3	Expanded inspection	0.005360	0.994640
Germany	Y2016	1to3	More detailed inspection	0.004060	0.995940
Germany	Y2016	4to9	Initial inspection	0.004008	0.995992
Germany	Y2016	4to9	Expanded inspection	0.996644	0.003356
Germany	Y2016	4to9	More detailed inspection	0.003861	0.996139
Germany	Y2016	Morethan10	Initial inspection	0.493506	0.506493
Germany	Y2016	Morethan10	Expanded inspection	0.996097	0.003903
Germany	Y2016	Morethan10	More detailed inspection	0.995420	0.004580
Germany	Y2017	None	Initial inspection	0.003226	0.996774
Germany	Y2017	None	Expanded inspection	0.004467	0.995533
Germany	Y2017	None	More detailed inspection	0.004489	0.995511
Germany	Y2017	1to3	Initial inspection	0.003593	0.996407
Germany	Y2017	1to3	Expanded inspection	0.004088	0.995912
Germany	Y2017	1to3	More detailed inspection	0.003261	0.996739
Germany	Y2017	4to9	Initial inspection	0.003920	0.996081
Germany	Y2017	4to9	Expanded inspection	0.996516	0.003484
Germany	Y2017	4to9	More detailed inspection	0.996230	0.003770
Germany	Y2017	Morethan10	Initial inspection	0.484598	0.515402
Germany	Y2017	Morethan10	Expanded inspection	0.996492	0.003508
Germany	Y2017	Morethan10	More detailed inspection	0.997077	0.002923
Greece	Y2015	None	Initial inspection	0.003171	0.996828
Greece	Y2015	None	Expanded inspection	0.003988	0.996012

Greece	Y2015	None	More detailed inspection	0.004304	0.995696
Greece	Y2015	1to3	Initial inspection	0.003937	0.996063
Greece	Y2015	1to3	Expanded inspection	0.004157	0.995843
Greece	Y2015	1to3	More detailed inspection	0.004558	0.995442
Greece	Y2015	4to9	Initial inspection	0.003324	0.996676
Greece	Y2015	4to9	Expanded inspection	0.003916	0.996084
Greece	Y2015	4to9	More detailed inspection	0.004311	0.995689
Greece	Y2015	Morethan10	Initial inspection	0.561434	0.438566
Greece	Y2015	Morethan10	Expanded inspection	0.995858	0.004142
Greece	Y2015	Morethan10	More detailed inspection	0.995822	0.004178
Greece	Y2016	None	Initial inspection	0.003714	0.996286
Greece	Y2016	None	Expanded inspection	0.004652	0.995348
Greece	Y2016	None	More detailed inspection	0.004262	0.995738
Greece	Y2016	1to3	Initial inspection	0.005111	0.994889
Greece	Y2016	1to3	Expanded inspection	0.003968	0.996032
Greece	Y2016	1to3	More detailed inspection	0.004324	0.995676
Greece	Y2016	4to9	Initial inspection	0.003597	0.996403
Greece	Y2016	4to9	Expanded inspection	0.002867	0.997133
Greece	Y2016	4to9	More detailed inspection	0.004206	0.995794
Greece	Y2016	Morethan10	Initial inspection	0.511858	0.488142
Greece	Y2016	Morethan10	Expanded inspection	0.997151	0.002849
Greece	Y2016	Morethan10	More detailed inspection	0.467093	0.532907
Greece	Y2017	None	Initial inspection	0.003454	0.996546
Greece	Y2017	None	Expanded inspection	0.004543	0.995457
Greece	Y2017	None	More detailed inspection	0.003311	0.996688
Greece	Y2017	1to3	Initial inspection	0.003857	0.996143
Greece	Y2017	1to3	Expanded inspection	0.003981	0.996019
Greece	Y2017	1to3	More detailed inspection	0.004211	0.995789
Greece	Y2017	4to9	Initial inspection	0.004324	0.995676
Greece	Y2017	4to9	Expanded inspection	0.003366	0.996634

Greece	Y2017	4to9	More detailed inspection	0.003025	0.996975
Greece	Y2017	Morethan10	Initial inspection	0.461432	0.538568
Greece	Y2017	Morethan10	Expanded inspection	0.996726	0.003274
Greece	Y2017	Morethan10	More detailed inspection	0.995970	0.004029
Italy	Y2015	None	Initial inspection	0.004109	0.995891
Italy	Y2015	None	Expanded inspection	0.004759	0.995241
Italy	Y2015	None	More detailed inspection	0.003341	0.996659
Italy	Y2015	1to3	Initial inspection	0.003757	0.996243
Italy	Y2015	1to3	Expanded inspection	0.002981	0.997019
Italy	Y2015	1to3	More detailed inspection	0.003659	0.996341
Italy	Y2015	4to9	Initial inspection	0.003786	0.996214
Italy	Y2015	4to9	Expanded inspection	0.996957	0.003043
Italy	Y2015	4to9	More detailed inspection	0.995685	0.004315
Italy	Y2015	Morethan10	Initial inspection	0.476410	0.523590
Italy	Y2015	Morethan10	Expanded inspection	0.996170	0.003830
Italy	Y2015	Morethan10	More detailed inspection	0.995739	0.004261
Italy	Y2016	None	Initial inspection	0.003553	0.996447
Italy	Y2016	None	Expanded inspection	0.004660	0.995340
Italy	Y2016	None	More detailed inspection	0.003241	0.996759
Italy	Y2016	1to3	Initial inspection	0.003751	0.996249
Italy	Y2016	1to3	Expanded inspection	0.003296	0.996704
Italy	Y2016	1to3	More detailed inspection	0.004040	0.995960
Italy	Y2016	4to9	Initial inspection	0.004738	0.995262
Italy	Y2016	4to9	Expanded inspection	0.003959	0.996041
Italy	Y2016	4to9	More detailed inspection	0.004701	0.995299
Italy	Y2016	Morethan10	Initial inspection	0.506178	0.493822
Italy	Y2016	Morethan10	Expanded inspection	0.996145	0.003855
Italy	Y2016	Morethan10	More detailed inspection	0.995801	0.004199
Italy	Y2017	None	Initial inspection	0.003664	0.996336
Italy	Y2017	None	Expanded inspection	0.003189	0.996811

Italy	Y2017	None	More detailed inspection	0.003587	0.996413
Italy	Y2017	1to3	Initial inspection	0.003376	0.996624
Italy	Y2017	1to3	Expanded inspection	0.003278	0.996722
Italy	Y2017	1to3	More detailed inspection	0.003255	0.996745
Italy	Y2017	4to9	Initial inspection	0.003444	0.996556
Italy	Y2017	4to9	Expanded inspection	0.996004	0.003996
Italy	Y2017	4to9	More detailed inspection	0.004040	0.995960
Italy	Y2017	Morethan10	Initial inspection	0.484736	0.515264
Italy	Y2017	Morethan10	Expanded inspection	0.996580	0.003421
Italy	Y2017	Morethan10	More detailed inspection	0.995777	0.004223
Netherlands	Y2015	None	Initial inspection	0.003774	0.996226
Netherlands	Y2015	None	Expanded inspection	0.004955	0.995045
Netherlands	Y2015	None	More detailed inspection	0.003583	0.996417
Netherlands	Y2015	1to3	Initial inspection	0.005318	0.994682
Netherlands	Y2015	1to3	Expanded inspection	0.004007	0.995993
Netherlands	Y2015	1to3	More detailed inspection	0.003715	0.996285
Netherlands	Y2015	4to9	Initial inspection	0.003709	0.996291
Netherlands	Y2015	4to9	Expanded inspection	0.003163	0.996837
Netherlands	Y2015	4to9	More detailed inspection	0.004276	0.995724
Netherlands	Y2015	Morethan10	Initial inspection	0.554601	0.445399
Netherlands	Y2015	Morethan10	Expanded inspection	0.995449	0.004551
Netherlands	Y2015	Morethan10	More detailed inspection	0.995835	0.004165
Netherlands	Y2016	None	Initial inspection	0.003253	0.996746
Netherlands	Y2016	None	Expanded inspection	0.003566	0.996435
Netherlands	Y2016	None	More detailed inspection	0.004713	0.995287
Netherlands	Y2016	1to3	Initial inspection	0.003597	0.996403
Netherlands	Y2016	1to3	Expanded inspection	0.005138	0.994862
Netherlands	Y2016	1to3	More detailed inspection	0.004411	0.995589
Netherlands	Y2016	4to9	Initial inspection	0.004709	0.995291
Netherlands	Y2016	4to9	Expanded inspection	0.003701	0.996299

Netherlands	Y2016	4to9	More detailed inspection	0.004005	0.995995
Netherlands	Y2016	Morethan10	Initial inspection	0.003219	0.996781
Netherlands	Y2016	Morethan10	Expanded inspection	0.996249	0.003751
Netherlands	Y2016	Morethan10	More detailed inspection	0.995352	0.004648
Netherlands	Y2017	None	Initial inspection	0.003621	0.996379
Netherlands	Y2017	None	Expanded inspection	0.004879	0.995121
Netherlands	Y2017	None	More detailed inspection	0.004316	0.995684
Netherlands	Y2017	1to3	Initial inspection	0.003735	0.996265
Netherlands	Y2017	1to3	Expanded inspection	0.004371	0.995628
Netherlands	Y2017	1to3	More detailed inspection	0.002932	0.997069
Netherlands	Y2017	4to9	Initial inspection	0.004090	0.995910
Netherlands	Y2017	4to9	Expanded inspection	0.003900	0.996100
Netherlands	Y2017	4to9	More detailed inspection	0.004105	0.995895
Netherlands	Y2017	Morethan10	Initial inspection	0.003591	0.996409
Netherlands	Y2017	Morethan10	Expanded inspection	0.996908	0.003092
Netherlands	Y2017	Morethan10	More detailed inspection	0.996321	0.003679
Spain	Y2015	None	Initial inspection	0.003381	0.996619
Spain	Y2015	None	Expanded inspection	0.003012	0.996988
Spain	Y2015	None	More detailed inspection	0.003356	0.996644
Spain	Y2015	1to3	Initial inspection	0.004245	0.995755
Spain	Y2015	1to3	Expanded inspection	0.004013	0.995987
Spain	Y2015	1to3	More detailed inspection	0.004999	0.995001
Spain	Y2015	4to9	Initial inspection	0.003946	0.996054
Spain	Y2015	4to9	Expanded inspection	0.003243	0.996757
Spain	Y2015	4to9	More detailed inspection	0.003220	0.996780
Spain	Y2015	Morethan10	Initial inspection	0.558074	0.441926
Spain	Y2015	Morethan10	Expanded inspection	0.995809	0.004191
Spain	Y2015	Morethan10	More detailed inspection	0.996274	0.003726
Spain	Y2016	None	Initial inspection	0.003787	0.996213
Spain	Y2016	None	Expanded inspection	0.004016	0.995984

Spain	Y2016	None	More detailed inspection	0.004230	0.995770
Spain	Y2016	1to3	Initial inspection	0.003490	0.996510
Spain	Y2016	1to3	Expanded inspection	0.004097	0.995903
Spain	Y2016	1to3	More detailed inspection	0.003407	0.996593
Spain	Y2016	4to9	Initial inspection	0.003384	0.996616
Spain	Y2016	4to9	Expanded inspection	0.003463	0.996537
Spain	Y2016	4to9	More detailed inspection	0.003359	0.996641
Spain	Y2016	Morethan10	Initial inspection	0.511028	0.488972
Spain	Y2016	Morethan10	Expanded inspection	0.995572	0.004428
Spain	Y2016	Morethan10	More detailed inspection	0.996374	0.003626
Spain	Y2017	None	Initial inspection	0.002904	0.997096
Spain	Y2017	None	Expanded inspection	0.003140	0.996860
Spain	Y2017	None	More detailed inspection	0.004077	0.995923
Spain	Y2017	1to3	Initial inspection	0.003251	0.996749
Spain	Y2017	1to3	Expanded inspection	0.003153	0.996847
Spain	Y2017	1to3	More detailed inspection	0.004403	0.995597
Spain	Y2017	4to9	Initial inspection	0.003718	0.996282
Spain	Y2017	4to9	Expanded inspection	0.003452	0.996548
Spain	Y2017	4to9	More detailed inspection	0.002967	0.997033
Spain	Y2017	Morethan10	Initial inspection	0.529706	0.470294
Spain	Y2017	Morethan10	Expanded inspection	0.995537	0.004463
Spain	Y2017	Morethan10	More detailed inspection	0.995494	0.004506
UK	Y2015	None	Initial inspection	0.003929	0.996071
UK	Y2015	None	Expanded inspection	0.004734	0.995266
UK	Y2015	None	More detailed inspection	0.003081	0.996920
UK	Y2015	1to3	Initial inspection	0.003331	0.996669
UK	Y2015	1to3	Expanded inspection	0.004501	0.995499
UK	Y2015	1to3	More detailed inspection	0.003963	0.996037
UK	Y2015	4to9	Initial inspection	0.003667	0.996333
UK	Y2015	4to9	Expanded inspection	0.996620	0.003380

UK	Y2015	4to9	More detailed inspection	0.003359	0.996641
UK	Y2015	Morethan10	Initial inspection	0.528948	0.471052
UK	Y2015	Morethan10	Expanded inspection	0.996939	0.003061
UK	Y2015	Morethan10	More detailed inspection	0.996657	0.003343
UK	Y2016	None	Initial inspection	0.003120	0.996880
UK	Y2016	None	Expanded inspection	0.003366	0.996634
UK	Y2016	None	More detailed inspection	0.004119	0.995881
UK	Y2016	1to3	Initial inspection	0.004365	0.995635
UK	Y2016	1to3	Expanded inspection	0.003230	0.996770
UK	Y2016	1to3	More detailed inspection	0.003753	0.996247
UK	Y2016	4to9	Initial inspection	0.003699	0.996301
UK	Y2016	4to9	Expanded inspection	0.995960	0.004040
UK	Y2016	4to9	More detailed inspection	0.003015	0.996985
UK	Y2016	Morethan10	Initial inspection	0.452298	0.547702
UK	Y2016	Morethan10	Expanded inspection	0.995633	0.004367
UK	Y2016	Morethan10	More detailed inspection	0.996003	0.003997
UK	Y2017	None	Initial inspection	0.003586	0.996414
UK	Y2017	None	Expanded inspection	0.005043	0.994957
UK	Y2017	None	More detailed inspection	0.004027	0.995973
UK	Y2017	1to3	Initial inspection	0.003075	0.996925
UK	Y2017	1to3	Expanded inspection	0.004313	0.995687
UK	Y2017	1to3	More detailed inspection	0.003981	0.996019
UK	Y2017	4to9	Initial inspection	0.003638	0.996362
UK	Y2017	4to9	Expanded inspection	0.995778	0.004222
UK	Y2017	4to9	More detailed inspection	0.004144	0.995856
UK	Y2017	Morethan10	Initial inspection	0.004030	0.995970
UK	Y2017	Morethan10	Expanded inspection	0.996008	0.003992
UK	Y2017	Morethan10	More detailed inspection	0.996477	0.003523

Table Appendix 2.10. CPT of 'Detention'

Vessel group	Inspection group	Yes	No
High Detention Risk	High Detention Risk	0.587624	0.412375
High Detention Risk	Low Detention Risk	0.062388	0.937612
Low Detention Risk	High Detention Risk	0.172431	0.827569
Low Detention Risk	Low Detention Risk	0.004550	0.995450